

Large-scale Unit Commitment under uncertainty

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Abstract The Unit Commitment problem in energy management aims at finding the optimal production schedule of a set of generation units while meeting various system-wide constraints. It has always been a large-scale, non-convex difficult problem, especially in view of the fact that operational requirements imply that it has to be solved in an unreasonably small time for its size. Recently, the ever increasing capacity for renewable generation has strongly increased the level of uncertainty in the system, making the (ideal) Unit Commitment model a large-scale, non-convex, *uncertain* (stochastic, robust, chance-constrained) program. We provide a survey of the literature on methods for the Uncertain Unit Commitment problem, in all its variants. We start with a review of the main contributions on solution methods for the deterministic versions of the problem, focusing on those based on mathematical programming techniques that are more relevant for the uncertain versions of the problem. We then present and categorize the approaches to the latter, also providing entry points to the relevant literature on optimization under uncertainty.

Keywords Unit Commitment · Uncertainty · Large-Scale Optimization · Survey

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41 1 Introduction

42 In electrical energy production and distribution systems, an important problem deals with computing
43 the production schedule of the available generating units in order to meet their technical and opera-
44 tional constraints and to satisfy some system-wide constraints, e.g., global equilibrium between energy
45 production and energy demand. The constraints of the units are very complex; for instance, some units
46 may require up to 24 hours to start. Therefore, such a schedule must be computed (well) in advance of
47 real time. The resulting family of models is usually referred to as the *Unit Commitment* problem (UC),
48 and its practical importance is clearly proven by the enormous amount of scientific literature devoted
49 to its solution in the last four decades and more. Besides the very substantial practical and economical
50 impact of UC, this proliferation of research is motivated by at least two independent factors:

- 51 1. on the one hand, progress in optimization methods, which provides novel methodological approaches
52 and improves the performances of existing ones, thereby allowing to tackle previously unsolvable
53 problems;
- 54 2. on the other hand, the large variety of different versions of UC corresponding to the disparate
55 characteristics of electrical systems worldwide (free market vs. centralized, vast range of production
56 units due to hydro/thermal/nuclear sources, ...).

57 Despite all of this research, UC still cannot be considered a “well-solved” problem. This is partly due to
58 the need of continuously adapting to the ever-changing demands of practical operational environments,
59 in turn caused by technological and regulatory changes which significantly alter the characteristics of
60 the problem to be solved. Furthermore, UC is a large-scale, non-convex optimization problem that,
61 due to the operational requirements, has to be solved in an “unreasonably” small time. Finally, as
62 methodological and technological advances make previous versions of UC more accessible, practitioners
63 have a chance to challenge the (very significant) simplifications that have traditionally been made,
64 for purely computational reasons, about the actual behavior of generating units. This leads to the
65 development of models incorporating considerable more detail than in the past, which can significantly
66 stretch the capabilities of current solution methods.

67 A particularly relevant recent trend in electrical systems is the ever increasing use of intermittent (renew-
68 able) production sources such as wind and solar power. This has significantly increased the underlying

69 *uncertainty* in the system, previously almost completely due to variation of users' demand (which could
70 however be forecast quite effectively) and occurrence of faults (which was traditionally taken into account
71 by requiring some amount of spinning reserve). Ignoring such a substantial increase in uncertainty levels
72 w.r.t. the common existing models incurs an unacceptable risk that the computed production schedules
73 be significantly more costly than anticipated, or even infeasible (e.g., [205]). However, incorporating the
74 uncertainty in the models is very challenging, in particular in view of the difficulty of the *deterministic*
75 versions of UC.

76 Fortunately, optimization methods capable of dealing with uncertainty have been a very active area of
77 research in the last decade, and several of these developments can be applied, and have been applied, to
78 the UC problem. This paper aims at providing a survey of approaches for the *Uncertain* UC problem
79 (UUC). To the best of our knowledge no such survey exists, while the literature is rapidly growing. This
80 is easily explained, besides by the practical significance of UUC, by the combination of two factors: on
81 one hand the diversity of operational environments that need to be considered, and on the other hand
82 by the fact that the multitude of applicable solution techniques already available to the UC (here and
83 in the following we mean the deterministic version when UUC is not explicitly mentioned) is further
84 compounded by the need of deciding *how uncertainty is modeled*. Indeed, the literature offers at least
85 three approaches that have substantially different practical and computational requirements: *Stochastic*
86 *Optimization* (SO), *Robust Optimization* (RO), and *Chance-Constrained Optimization* (CCO). This
87 modeling choice has vast implications on the actual form of UUC, its potential robustness in the face
88 of uncertainty, the (expected) cost of the computed production schedules and the computational cost
89 of determining them. Hence, UUC is even less "well-solved" than UC, and a thriving area of research.
90 Therefore, a survey about it is both timely and appropriate.

91 We start with a review of the main recent contributions on solution methods for UC that have an impact
92 on those for the uncertain version. This is necessary, as the last broad UC survey [290] dates back some
93 10 years, and is essentially an update of [349]; neither of these consider UUC in a separate way as we
94 do. The more recent survey [127] provides some complements to [290] but it does not comprehensively
95 cover methods based on mathematical programming techniques, besides not considering the uncertain
96 variants. The very recent survey [337] focuses mainly on nature-inspired or evolutionary computing
97 approaches, most often applied to simple 10-units systems which can nowadays be solved optimally
98 in split seconds with general-purpose techniques; furthermore these methods do not provide qualified
99 bounds (e.g., optimality gap) that are most often required when applying SO, RO or CCO techniques to
100 the solution of UUC. This, together with the significant improvement of solving capabilities of methods
101 based on mathematical programming techniques (e.g., Lagrangian or Benders' decomposition methods,
102 Mixed Integer Linear Programming approaches, ...), justifies why in the UC-part of our survey we
103 mostly focus on the latter rather than on heuristic approaches.

104 Because the paper surveys such a large variety of material, we provide two different *reading maps* to the
105 readers:

- 106 1. The first is the standard reading order of the paper, synthesized in the Table of Contents above.
107 In Section 2 we describe the varied technical and operational constraints in (U)UC models which
108 give rise to many different variants of UC problems. In Section 3 we provide an overview of methods
109 that deal with the deterministic UC, focusing in particular onto methods dealing with large-scale
110 systems and/or that can be naturally extended to UUC, at least as subproblems. In particular, in
111 §3.1 we discuss Dynamic Programming approaches, in §3.2 we discuss Integer and Mixed Integer Lin-
112 ear Programming (MILP) approaches, while in §3.3 and §3.4 we discuss decomposition approaches
113 (Lagrangian, Benders' and Augmented Lagrangian), and finally in §3.5 we (quickly) discuss (Meta-)
114 Heuristics. UUC is then the subject of Section 4: in particular, §4.2 presents Stochastic Optimiza-
115 tion (Scenario-Tree) approaches, §4.3 presents Robust Optimization approaches, and §4.4 presents
116 Chance-Constrained Optimization approaches. We end the paper with some concluding remarks in
117 §5, and with a list of the most used acronyms.
- 118 2. The second map is centered on the different algorithmic approaches that have been used to solve
119 (U)UC. The main ones considered in this review are:

- 120 – *Dynamic Programming* approaches, which can be found in §3.1, §3.2.2, §3.3, §3.5.2, §4.1.1.1,
- 121 §4.2.1, §4.2.3, §4.2.4, and §4.4;
- 122 – *Mixed-Integer Programming* approaches, which can be found in §3.2, §3.3, §4.1.2.2, §4.2, §4.2.1,
- 123 §4.2.3, §4.2.4, §4.3, and §4.4;
- 124 – *Lagrangian Relaxation* (decomposition) approaches, which can be found in §3.2.2, §3.3, §3.5.2,
- 125 §4.2.1, §4.2.2, §4.2.3, §4.2.4, and §4.4;
- 126 – *Benders’ decomposition* approaches, which can be found in §3.2.2, §3.3, §4.2, §4.2.1, §4.2.2, §4.2.3,
- 127 §4.2.4, and §4.3;
- 128 – *Augmented Lagrangian* approaches, which can be found in §3.3, §3.4, and §4.4;
- 129 – other forms of *heuristic* approaches, which can be found in §3.1, §3.2.2, §3.3, §3.5, §4.1.2.1, §4.2.2,
- 130 and §4.2.3.

131 2 Ingredients of the Unit Commitment problem

132 We start our presentation with a very short description of the general structure of electrical systems,
 133 presenting the different decision-makers who may find themselves in the need of solving (U)UC problems
 134 and their interactions. This discussion will clarify which of the several possible views and needs we will
 135 cover; the reader with previous experience in this area can skip to §2.1 for a more detailed presentation of
 136 the various ingredients of the (U)UC model, or even to §3 for the start of the discussion about algorithmic
 137 approaches.

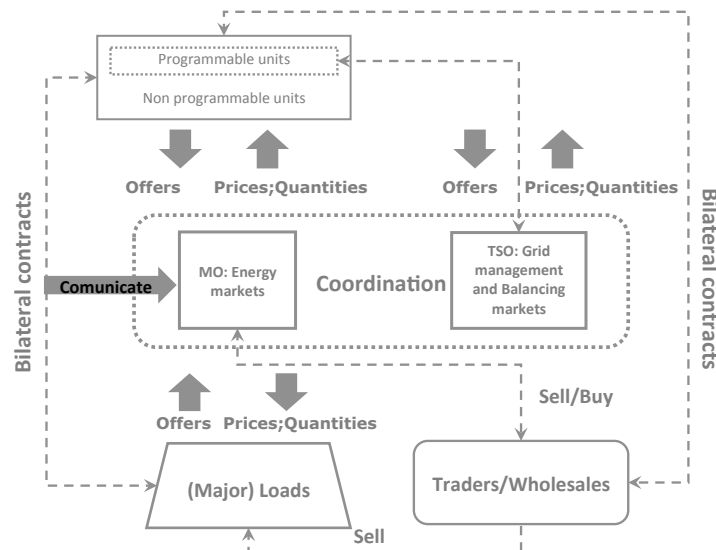


Fig. 1 Simplified electricity market structure

138 When the first UC models were formulated, the usual setting was that of a Monopolistic Producer (MP).
 139 The MP was in charge of the electrical production, transmission and distribution in one given area, often
 140 corresponding to a national state, comprised the regulation of exchanges with neighbouring regions. In
 141 the liberalized markets that are nowadays prevalent, the decision chain is instead decentralized and
 142 significantly more complex, as shown in the (still somewhat simplified) scheme of Figure 1. In a typical
 143 setting, companies owning generation assets (GENCOs) have to bid their generation capacity over one (or
 144 more) Market Operator(s) (MO). Alternatively, or in addition, they can stipulate bilateral contracts (or
 145 contracts for differences, CfD) with final users or with wholesales/traders. Once received the bids/offers,
 146 the MO clears the (hourly) energy market and defines (equilibrium) clearing prices. A Transmission
 147 System Operator (TSO), in possession of the transmission infrastructure, then has the duty—acting
 148 in concert with the Power Exchange Manager (PEM)—to ensure safe delivery of the energy, which in
 149 turns means different duties such as real time frequency-power balancing, spinning reserve satisfaction,
 150 voltage profile stability, and enforcing real-time network capacity constraints. The TSO typically operates

151 in a different way programmable and non programmable units, since for instance only the former can
 152 participate to balancing markets.

153 This basic setting, which can be considered sufficient for our discussion, is only a simplification of the
 154 actual systems, which also vary depending on their geographical position. For instance, transmission (and
 155 distribution) assets may actually be in possession of different companies that have to offer them under
 156 highly regulated fair and non-discriminative conditions, leaving the TSO only a coordination role. Also,
 157 the TSO and the MO may or may not be the same entity, and so on. We leave aside these other factors,
 158 like how many and MOs there are and how exactly these are structured; we refer to [94, 173, 281, 346] [91,
 159 Chapter 1] for a more detailed description. Because of this complexity, standard optimization models
 160 may not be entirely appropriate to deal with all the aspects of the problem, since the behavior of
 161 different/competing decision makers need be taken into account. This may require the use of other
 162 methodologies, such as the computation of equilibria or agent-based simulation. We will not deal with
 163 any of these aspects, the interested reader being referred to [149, 173, 224, 281, 346, 386] for further
 164 discussion.

165 2.1 A global view of UC

166 In broad terms, the (deterministic or uncertain) Unit Commitment problem (both UC in this section
 167 unless explicitly stated) requires to minimize the cost, or maximize the benefit, obtained by the pro-
 168 duction schedule for the available generating units over a given time horizon. As such, the fundamental
 169 ingredients of UC are its objective function and its constraints. Of course, another fundamental ingredi-
 170 ent is the time horizon itself; UC being a short-term model this is most often a day or two of operations,
 171 and up to a week. In the following we will denote it by \mathcal{T} , which is typically considered to be a discrete
 172 set corresponding to a finite number of *time instants* $t \in \mathcal{T}$, usually hours or half-hours (down to 15 or
 173 5 minutes). Thus, the typical size of \mathcal{T} varies from 24 to a few hundred.

174 In mathematical terms, UC has the general structure

$$\min \{ f(x) : x \in X_1 \cap X_2, \} \quad (1)$$

175 where $x \in \mathbb{R}^n$ is the decision making vector. Usually (most) elements of x are indexed according to both
 176 the generating unit $i = 1, \dots, m$ and the time instant $t \in \mathcal{T}$ they refer to. Thus, one often speaks of the
 177 subvectors x^t of all decisions pertaining to time t and/or x_i of all decisions pertaining to unit i . Also,
 178 entries of x are typically split among:

- 179 1. *commitment decision*, discrete variables that determine if a particular unit is on or off at any given
 180 time (often denoted by u_i^t);
- 181 2. *production decision*, continuous variables that provide the amount of generated power by a specific
 182 unit at a given time (often denoted by p_i^t);
- 183 3. *network decision*, such as these representing phase angle or voltage magnitudes, describing the state
 184 of the transmission or distribution network.

185 A UC problem not having commitment decisions is often called Economic Dispatch (ED) (e.g. [426])
 186 or Optimal Power Flow (OPF) when the network is considered, (e.g. [193]). It could be argued that
 187 commitment decisions can be easily derived from production decisions (each time a non-zero production
 188 output is present the unit has to be on), but for modeling purposed it is useful to deal with the two
 189 different concepts separately, cf. §3.2. Besides, the point is that in ED or OPF the commitment of units
 190 has already been fixed and cannot be changed. We remark that network decisions may also include binary
 191 variables that provide the open or close state of a particular line, as entirely closing a line is one of the
 192 few options that the physic of electrical networks allows for “routing” the electrical current (cf. §2.7).
 193 While ED can be expected to be simpler than UC, and in many cases it is a simple convex program
 194 that can nowadays be solved with off-the-shelf techniques, this is not always the case. ED was not only
 195 challenging in the past (e.g., [109] and the references therein), but can still be do so today. Indeed, even

when commitment decisions are fixed, the electrical system is highly nonlinear and nonconvex, e.g., due to hydro units efficiency curves (cf. §2.4) or the transmission network characteristics (cf. §2.6), so that ED can still be a nontrivial problem that may require ad-hoc approaches (e.g. [185, 192, 193, 213, 254, 279]).

In equation (1), X_1 is the set modeling all *technical/operational constraints of the individual units* and X_2 are the *system-wide constraints*. The first set is by definition structured as a Cartesian product of smaller sets, i.e., $X_1 = \prod_{i=1}^m X_i^1$, with $X_i^1 \subseteq \mathbb{R}^{n_i}$ and $\sum_{i=1}^m n_i = n$. Moreover, the objective function f typically also allows for a decomposition along the sets X_i^1 , i.e., $f(x) = \sum_{i=1}^m f_i(x_i)$ and $x_i \in X_i^1$. Each of the sets X_i^1 roughly contains the feasible production schedules for one unit, that can differ very significantly between different units due to the specific aspects related to their technological and operational characteristics. In most models, X_1 is non-convex. However, units sharing the same fundamental operational principles often share a large part of their constraints as well. Because of this, these constraints are best described according to the *type* of the generating unit, i.e.,

1. thermal units (cf. §2.3);
2. hydro units (cf. §2.4);
3. renewable generation units (cf. §2.3–2.5).

While hydro units are arguably a part of renewable generation, in the context of UC it is fundamental to distinguish between those units that are programmable and those that are not. That is, hydroelectric generation systems relying on a flow that can not be programmed are to be counted among renewable generation ones together with solar and wind-powered ones. This is unless these so-called *run-of-river* (ROR) units are part of a *hydro valley*, preceded by a programmable hydro one (cf. §2.4).

The set X_2 , which usually models at least the offer-demand equilibrium constraints, is most often, but not always, convex and even polyhedral. This set may also incorporate other system-wide constraints, such as emission constraints, network transmission constraints (cf. §2.6) or optimal transmission switching constraints (cf. §2.7).

Solving (1) is difficult when n is large (which usually means that m is large) or X_1 is a complex set; the latter occurs e.g. when substantial modeling detail on the operations of units is integrated in the model. Finally, (1) contains no reference to uncertainty, but several sources of uncertainty are present in actual operational environments, as summarized in the following table:

Data	Uncertain for	Severity
customer load	GENCOs, TSO	low/medium
reservoirs inflows	GENCOs, TSO	medium
renewable generation	GENCOs, TSO	high
prices/quantities	GENCOs, traders, customers	medium/high
units/network failure	GENCOs, TSO	medium

Various ways to incorporate uncertainty in (1) are discussed in §4.1. Obviously, solving (1) becomes more difficult when uncertainty is present, even when n is small and X_1 relatively simple. Thus, properly exploiting the structure of the problem (the function f and the sets X_1 and X_2) is crucial to obtain efficient schemes for UC, and even more so for UUC. This is why we now provide some detail on different modeling features for each of these components.

2.2 The objective function

The objective function of UC is one of the main factors reflecting the different types of decision-makers described in the previous section. In fact, when the production needs to be satisfied (as in the case of the MP, or of a GENCO having had a certain set of bids accepted) the objective function fundamentally aims at *minimizing energy production costs*; this is not necessarily obvious (cf. the case of hydro units below), but the principle is clear. However, in the free-market regime the aim is typically rather to

236 *maximize energy production profits*. This again requires estimating the costs, so the same objective as in
 237 the MP case largely carries over, but it also requires estimating the revenues from energy selling, as it is
 238 the difference between the two that has to be maximized. In particular, if the GENCO is a *price maker*
 239 it may theoretically indulge in *strategic bidding* [103], whereby the GENCO withdraws power from the
 240 market (by bidding it at high cost) in order to push up market prices, resulting in an overall diminished
 241 production from its units but higher profit due to the combined effect of decreased production cost and
 242 increased unitary revenue for the produced energy. Of course, the success of such a strategy depends on
 243 the (unknown) behavior of the other participants to the market, which thereby introduces significant
 244 uncertainty in the problem. The electrical market is also highly regulated to rule out such behavior of the
 245 market participants; in particular, larger GENCOs, being more easily price makers, are strictly observed
 246 by the regulator and bid all their available capacity on the market. Yet, the solution of *strategic bidding*
 247 *problems* is of interest at least to the regulators themselves, who need to identify the GENCOs who may
 248 in principle exercise market power and identify possible patterns of abuse. Even in the *price taker* case,
 249 i.e., a GENCO with limited assets and little or no capacity to influence market prices, uncertainty is
 250 added by the need of accurately predicting the selling price of energy for each unit and each $t \in \mathcal{T}$ [156].
 251 This uncertainty must then be managed, e.g. with techniques such as those of Robust Optimization [30].

252 Energy production costs for fuel-burning units are typically modeled (in increasing order of complexity)
 253 as linear, piecewise-linear convex, quadratic convex, or nonconvex functions separable for each $t \in \mathcal{T}$.
 254 In fact, while the fuel-consumption-to-generated-power curve can usually be reasonably well approxi-
 255 mated with a piecewise linear function or a low-order polynomial one, other technical characteristics of
 256 generating systems introduce nonconvex elements. The simplest form is that of a *fixed cost* to be paid
 257 whenever the unit is producing at some $t \in \mathcal{T}$, irrespective of the actual amount of generated power.
 258 In alternative, or in addition, *start-up costs* (and, less frequently, shut-down ones) are incurred when a
 259 unit is brought online after a period of inactivity. In their simplest form start-up costs can be considered
 260 fixed, but most often they significantly depend on the time the unit has been off before having been
 261 restarted, and therefore are not separable for each time instant. The dependency of the start-up cost
 262 on time can be rather complex, as it actually depends on the choice between the unit being entirely
 263 de-powered (cooling) or being kept at an appropriate temperature, at the cost of burning some amount
 264 of fuel during the inactivity period, to make the start-up cheaper (banking). Technically speaking, in the
 265 latter case one incurs in a higher *boiler cost* to offset part of the *turbine cost*. The choice between these
 266 two alternatives can often be optimally made by simple formulæ once the amount of idle time is known,
 267 but this is typically not true beforehand in UC since the schedule of the unit is precisely the output of the
 268 optimization problem. Fortunately, some of the solution methods allow inclusion of the start-up cost at
 269 a relatively minor increase of the computational complexity; this is the case e.g. of MILP formulations,
 270 cf. §3.2, exploiting the fact that the optimal start-up cost is nondecreasing as the length of the idle period
 271 increases [75, 277]). In other cases start-up cost have basically no additional computational cost, such as
 272 in DP approaches, cf. §3.1. Other relevant sources of nonconvexity in the objective function are *valve*
 273 *points* [406], corresponding to small regions of the feasible production levels where the actual working of
 274 the unit is unstable, e.g. due to transitioning between two different configurations in a combined-cycle
 275 unit or other technical reasons, and that therefore should be avoided.

276 Nuclear units are generally considered thermal plants, although they significantly differ in particular
 277 for the objective function. Indeed, fuel cost has a different structure and depends on many factors, not
 278 only technical but also political (e.g., [112]). For convenience, formulæ similar to that of conventional
 279 thermal plants are often used. However, these units incur additional significant *modulation costs* whenever
 280 variations of power output are required; this cost is therefore again not separable per time instant.

281 Hydro units are generally assumed to have zero energy production cost, although they may in principle
 282 have crew and manning costs. In the self-scheduling case, where profit has to be maximized, this would
 283 lead to units systematically depleting all the available water due to the fact that a short-term model
 284 such as UC has no “visibility” on what happens after the end of its time horizon \mathcal{T} (the so-called “border
 285 effect”). Because of this, often a *value of water* coefficient is added to the objective function to represent
 286 the expected value of reserves left in the reservoirs at the end of \mathcal{T} . These values, as well as the required
 287 reservoir levels (cf. 2.4), are usually computed by means of specific mid-term optimization models. A very

standard approach is to value the differential between the initial and end volume of a reservoir against a volume-dependent water value; we refer to [80, 381] for details on various other modeling choices. A particular difficulty appears when we wish to integrate the water head effect on turbinning efficiency (e.g., [132, 316]), since this is typically a nonlinear and nonconvex relationship.

In general, the case of profit maximization requires knowledge of the selling and buying price of energy at each $t \in \mathcal{T}$. Because UC is solved ahead of actual operations, possibly precisely with the aim of computing the bids that will contribute to the setting of these prices (cf. e.g. [60, 65, 210, 320]), this requires nontrivial forecast models in order to obtain reasonable estimates of the prices (e.g. [226, 286, 419]). Depending on the time horizon and specific application, different price models can be considered. These can be obtained from time series modeling (e.g. [117, 264, 300]), mathematical finance (e.g. [45, 186, 271, 286, 302]) or can be based on electricity fundamentals (e.g. [122, 384]). For the case where the producer is a *price taker*, that is, small enough so that its production can be deemed to have little or no effect on the realized prices, UC can typically be independently solved for each individual unit (thus being styled as the *self-scheduling* problem), and it is therefore much easier [16], although uncertainty in prices then becomes a critical factor [30, 93, 275]. Things are significantly different in case the producer can exercise market power, that is, influence (increase) the prices by changing (withdrawing) the power it offers to the market; modeling this effect “ties” all the units back again into an unique UUC [65, 92, 105, 303]. Uncertainty in this case is also very relevant, with the behavior of competitors being one obvious primary source [7, 307, 389, 396, 401]. The matter is further complicated by the fact that the structure of the PE is usually complex, with more than one auction solved in cascade to account for different kinds of generation (energy, reserve, ancillary services, ...) [23, 370, 395] and by the fact that tight transmission constraints may create *zonal or even nodal prices*, thereby allowing producers who may not have market power in the global context to be able to exercise it in a limited region [227, 301, 303].

2.3 Thermal units

A thermal power station is a power plant in which the prime mover is steam driven. Technical/operational constraints can be classified as either *static* or *dynamic*: the former hold on each time step, whereas the latter link different (most often adjacent) time steps. Most typical static constraints are:

1. Offline: when the unit is offline, the power output is less than or equal to zero (negative power output refers to the power used by auxiliary installations, e.g., for nuclear plants).
2. Online: when the unit is online, the power output must be between Minimal Stable Generation (MSG) and maximal power output.
3. Starting: the unit is ramping up to MSG. The ramping profile depends on the number of hours a unit has been offline (e.g. [214]); see also in starting curve below. A unit in this state can in principle still be disconnected for a later start, but at a cost.
4. Stopping: the unit ramps down from MSG to the offline power output. As for starting, the ramping profile depends on the number of hours a unit has been online; see below in stopping curve.
5. Generation capacity: the production capacity of each unit. For some units the production output has to be selected among a discrete set of values.
6. Spinning reserve: the extra generating capacity that is available by increasing the power output of generators that are already connected to the power system. For most generators, this increase in power output is achieved by increasing the torque applied to the turbine’s rotor. Spinning reserves can be valued separately from actively generated power as they represent the main mechanism that electrical systems have to cope with real-time variations in demand levels.
7. Crew constraint: number of operators available to perform the actions in a power plant.

Typical dynamic constraints instead are:

1. Minimum Up/Down Time: a unit has to remain online/offline for at least a specific amount of time.

-
- 334 2. Operating Ramp Rate (also known as ramp-down and ramp-up rate): the increment and decrement
335 of the generation of a unit from a time step to another, excluding start-up and shut-down periods,
336 must be bounded by a constant (possibly different for ramp-up and ramp-down).
 - 337 3. Minimum Stable State Duration: a unit that has attained a specific generation level has to produce
338 at that level for a minimum duration of time.
 - 339 4. Maximum Numbers of Starts: the number of starts can be limited over a specific time horizon (such
340 a constraint is also implicitly imposed by Minimum Up/Down Time ones, and in fact the two are
341 often alternatives).
 - 342 5. Modulation and Stability: these constraints are mainly applied to an online nuclear unit. A unit is
343 *in modulation* if the output level changes in a time interval, whereas it is *stable* if the power level
344 remains identical to that of the previous time step. The constraints ensure that the unit is “most
345 often stable”, requiring that the number of modulations does not exceed a predefined limit over a
346 given time span (say, 24 hours).
 - 347 6. Starting (Stopping) Curve (also referred to in literature as start-up/shut-down ramp rate): in order to
348 start (stop) a unit and move it from the offline (online) state to the online (offline) state, the unit has
349 to follow a specific starting (stopping) curve, which links offline power output (zero, or negative for
350 nuclear plants) to MSG (or vice-versa) over the course of several time steps. Each starting (stopping)
351 curve implies a specific cost, and the chosen curve depends on the number of hours the plant has
352 been offline (online). Starting (stopping) may take anything from several minutes (and therefore be
353 typically irrelevant) up to 24 hours (and therefore be pivotal for the schedule).

354 2.4 Hydro units

355 Hydro units are in fact entire hydro valleys, i.e., a set of connected reservoirs, turbines and pumps that
356 influence each other through flow constraints. Turbines release water from uphill reservoirs to downhill
357 ones generating energy, pumps do the opposite. Note that the power output of ROR units downstream to
358 a reservoir (and up to the following reservoir, if any) must be counted together with that of the turbines
359 at the same reservoir; usually it is possible to do this by manipulating the power-to-discharged-water
360 curve of the unit at the reservoir, and thus ROR units in a hydro valley need not be explicitly modeled.
361 We remark in passing that whether or not a unit is considered ROR depends on the time horizon of the
362 problem: units with small reservoirs can be explicitly modeled in UC because they do have a degree of
363 modulation over the short term, but they may be considered ROR in longer-term problems since the
364 modulation is irrelevant over long periods of time.

365 As for thermal units, we distinguish constraints as being either static or dynamic. The typical ones of
366 the first kind are:

- 367 1. Reservoir Level: the level of water in each reservoir has to remain between a lower and upper bound.
368 Frequently these bounds are used to reflect strategic decisions corresponding to optimal long-term
369 use of water (cf. §2.2), and not necessarily reflect physical bounds. An alternative is to use a nonlinear
370 cost of water that reflects the higher risk incurred in substantially depleting the reservoir level, as
371 water in hydro reservoirs represents basically the only known way of efficiently storing energy on a
372 large scale and therefore provides a crucial source of flexibility in the system. Yet, bounds on the
373 level would ultimately be imposed anyway by physical constraints.
- 374 2. Bounds: turbines and pumps can operate only within certain bounds on the flowing water. In par-
375 ticular, some turbines might have a minimal production level akin to the MSG of thermal units.

376 The most common dynamic constraints are:

- 377 1. Flow Equations: these equations involve the physical balance of the water level in each reservoir and
378 connect the various reservoirs together. The reservoir levels get updated according to natural inflows,
379 what is turbined downhill, what is spilled downhill (i.e., let go from the reservoir to the next without
380 activating the turbines), and what is pumped from downhill to uphill. Spilling might not be allowed
381 for all reservoirs, nor all have pumping equipment.

-
- 382 2. Flow delay: the water flowing (uphill or downhill) from each unit to the next reservoir will reach it
383 after a given delay, that can possibly be of several hours (and occasionally even more [34]).
 - 384 3. Ramp Rate: adjacent turbinning levels have to remain sufficiently close to each other.
 - 385 4. Smooth Turbinning: over a a given time span (e.g., one hour), turbinning output should not be in
386 a V-shape, i.e., first increase and immediately afterwards decrease (or vice-versa). This constraint
387 is typically imposed to avoid excessive strain on the components, similarly to several constraints
388 on thermal units such as Minimum up/down Time, Maximum Numbers of Starts, Modulation and
389 Stability.
 - 390 5. Turbinning/Pumping Incompatibility: some turbines are reversible and therefore pumping and turbin-
391 ning cannot be done simultaneously. Moreover, switching from turbinning to pumping requires a certain
392 delay (e.g., 30 minutes). Some of these constraints actually only refer to a single time instant and
393 therefore they can be considered as static.
 - 394 6. Forbidden Zones: in complex hydro units, effects like mechanical vibrations and cavitation strongly
395 discourage using certain intervals of turbinned water, as these would result in low efficiency and/or
396 high output variation (similarly to valve points in thermal units, cf. §2.2). Therefore, constraints that
397 impose that the turbinned water lies outside of these forbidden zones might have to be imposed [130].

398 2.5 Renewable generation units

399 Renewable generation in UC mostly refers to wind farms, solar generation, stand alone ROR hydro
400 units, and geothermal production. The fundamental characteristic of all these sources, as far as UC is
401 concerned, is the fact that they cannot be easily modulated: the produced energy, and even if energy is
402 produced at all (in some wind farms energy is actually consumed to keep the blades in security when wind
403 blows too strongly), is decided by external factors. Some of these sources, most notably solar and wind,
404 are also characterized by their intermittency; that is, it is very difficult to provide accurate forecasts for
405 renewable generation, even for short time horizons (say, day-ahead forecasts). Furthermore, in several
406 cases renewable generation operates in a special regulatory regime implying that they cannot even be
407 modulated by disconnecting them from the grid. This has (not frequently, but increasingly often) led to
408 paradoxical situations where the spot price of energy is actually *negative*, i.e., one is paid to consume
409 the energy that renewable sources have the right to produce (and sell at fixed prices) no matter what
410 the demand actually is. All this has lead to significant changes in the operational landscape of energy
411 production systems, that can be summarized by the following factors:

- 412 1. The total renewable production cannot be predicted accurately in advance.
- 413 2. Renewable generation has high variance.
- 414 3. The correlation between renewable generation and the load can be negative, which is particularly
415 troublesome when load is already globally low, since significant strain is added to conventional gen-
416 eration assets which may have to quickly ramp down production levels, only to ramp them up (again
417 rapidly) not much later. This goes squarely against most of the standard operational constraints in
418 classical UC (cf. §2.3 and §2.4).

419 In other words, in UC terms renewable generation significantly complicates the problem; not so much
420 because it makes its size or structure more difficult, but because it dramatically increases the level of
421 uncertainty of net load (the load after the contribution of renewables is subtracted), forcing existing
422 generation units to serve primarily (or at least much more often than they were designed to) as backup
423 production in case of fluctuations, rather than as primary production systems. This increases the need
424 of flexible (hydro-)thermal units ready to guarantee load satisfaction at a short notice, which however
425 typically have a larger operational cost. We refer to [67, 252, 261, 341, 355] for further discussion of the
426 integration of renewable generation in UC.

 427 2.6 System-wide constraints

428 The most common form of system-wide constraints are the load constraints guaranteeing that global en-
 429 ergy demand is exactly satisfied for each $t \in \mathcal{T}$. This kind of constraint is not present in the self-scheduling
 430 version of UC where each unit reacts independently to price signals, but global load satisfaction has to
 431 be taken into account, sooner or later, even in liberalized market regimes. For instance, in several coun-
 432 tries, after the main energy market is cleared, GENCOs can swap demand between different units in
 433 order to better adjust the production schedules corresponding to the accepted bids to the operational
 434 constraints of their committed units, that are not completely represented in the auctions [318]. Alter-
 435 natively, or in addition, an *adjustment market* is ran where energy can be bought/sold to attain the
 436 same result [291, 340]. In both these cases the production schedules of all concerned units need be taken
 437 into account, basically leading back to global demand constraints. Also, in UC-based bidding systems
 438 the global impact of all the generation capacity of a GENCO on the energy prices need to be explicitly
 439 modeled, and this again leads to constraints linking the production levels of all units (at least, these
 440 of the given GENCO) that are very similar to standard demand constraints. Conversely, even demand
 441 constraints do not necessarily require the demand to be fully satisfied; often, *slacks* are added so that
 442 small amounts of deviation can be tolerated, albeit at a large cost (e.g., [119, 418]).

443 Another important issue to be mentioned is that the demand constraints need in general to take into
 444 account the shape and characteristics of the transmission network. These are typically modeled at three
 445 different levels of approximation:

- 446 – The *single bus model*: basically the network aspects are entirely disregarded and the demand is
 447 considered satisfied as soon as the total production is (approximately) equal to the total consumption,
 448 for each time instant, irrespectively of where these happen on the network. This corresponds to simple
 449 linear constraints and it is the most common choice in UC formulations.
- 450 – The *DC model* where the network structure is taken into account, including the capacity of the trans-
 451 mission links, but a simplified version of Kirchhoff laws is used so that the corresponding constraints
 452 are still linear, albeit more complex than in the bus model [137, 194, 218]. In [15] the concept of
 453 *umbrella constraints* is introduced to define a subset of the network DC constraints that are active
 454 in order to significantly reduce the size of these constraints.
- 455 – The *AC model* where the full version of Kirchhoff laws is used, leading to highly nonlinear and
 456 nonconvex constraints, so that even the corresponding ED becomes difficult [255, 256, 265, 356, 357].
 457 A recent interesting avenue of research concerns the fact that the non-convex AC constraints can
 458 be written as quadratic relations [192, 193, 213], which paves the way for convex relaxations using
 459 semidefinite programming approaches [254]. In particular, in the recent [187] a quadratic relaxation
 460 approach is proposed which builds upon the narrow bounds observed on decision variables (e.g. phase
 461 angle differences, voltage magnitudes) involved in power systems providing a formulation of the AC
 462 power flows equations that can be better incorporated into UC models with discrete variables, notably
 463 the ones of cf. §2.7. A recount of these recent developments can be found in [55].

464 Although market-based electrical systems have in some sense made network constraints less apparent to
 465 energy producers, they are nonetheless still very relevant nowadays; not only in the remaining vertically
 466 integrated electrical systems, but also for the TSO that handles network security and efficiency. This
 467 requires taking into account a fully detailed network model, even considering security issues such as $N - 1$
 468 fault resilience, together with a reasonably detailed model of GENCOs' units (comprising e.g. infra-hour
 469 power ramps, start-up costs, and start-up/shut-down ramp rate), when solving the Market Balancing
 470 problem. The latter is basically a residual demand, bidding-based UC. From a different perspective,
 471 network constraints might also be important for GENCOs that are able exercise market power in case
 472 *zonal or nodal pricing* is induced by the network structure [312].

473 Finally, both for vertically integrated system and in the TSO perspective, other relevant system-wide
 474 constraints are spinning reserve ones: the committed units must be able to provide some fraction (at
 475 least 3% according to [367]) of the total load in order to cope with unexpected surge of demand or
 476 failures of generating units and/or transmission equipment. Other global constraints linking all units,

477 or some subsets of them, exist: for instance, all (or specific subsets of) fossil-fuel burning units may
 478 have a maximum cap on the generation of pollutants (CO_2 , SO_x , NO_x , particles, ...) within the time
 479 horizon [148, 158, 190, 209, 399]. Alternatively, a cluster of geographically near units (a *plant*) burning
 480 the same fuel (typically gas) may be served by a unique reservoir, and can therefore share a constraint
 481 regarding the maximum amount of fuel that can be withdrawn from the reservoir within the time horizon
 482 [11, 12, 87, 148, 369]. Finally, there may be constraints on the minimum time between two consecutive
 483 start-ups in the same plant [119], e.g., due to crew constraints. If a plant comprises a small enough
 484 number of units it could alternatively be considered as a single “large” unit, so that these constraints
 485 become technical ones of this aggregated generator. The downside is that the problem corresponding to
 486 such a meta-unit then becomes considerably more difficult to solve.

487 2.7 Optimal Transmission Switching

488 Traditionally, in UC models the transmission network has been regarded as a “passive” element, whose
 489 role was just to allow energy to flow from generating units to demand points. This is also justified by
 490 the fact that electrical networks, unlike most other networks (logistic, telecommunications, gas, water,
 491 ...) are “not routable”: the current can only be influenced by changing nodal power injection, which
 492 is however partly fixed (at least as demand is concerned). Indeed, in traditional UC models there were
 493 no “network variables”, and the behavior of the transmission system was only modeled by constraints.
 494 However, as the previous paragraph has recalled, the transmission network is by far not a trivial element
 495 in the system, and separate network variables are required. Recently, the concept has been further
 496 extended to the case where the system behavior can be optimized by dynamically changing the *topology*
 497 of the network. This is a somewhat counterintuitive consequence of Kirchhoff laws: opening (interrupting)
 498 a line, maybe even a congested one, causes a global re-routing of electrical energy and may reduce the
 499 overall cost, e.g. by allowing to increase the power output of some cheaper (say, renewable) units [134].
 500 This effect can be especially relevant in those parts of the network with a high fraction of renewables
 501 whose production is sometimes cut off because of network constraints.

502 Thus, a new class of problems, called Optimal Transmission Switching (OTS) or System Topology
 503 Optimization (STO), has been defined whereby each line of the network has an associated binary decision
 504 (for each $t \in \mathcal{T}$) corresponding to the possibility of opening it. This makes the problem difficult to solve
 505 even with a very simple model of nodal injections and a simple network model such as the DC one
 506 (cf. §2.6); even more so with the AC model and a complete description of the generating units. The
 507 so-called UCOTS models [56, 134, 174–177, 207, 232, 233, 243, 280, 284, 285, 298, 327, 388, 420] extend UC:
 508 almost everything that can be said about UC is a fortiori valid for UCOTS, and therefore in the following
 509 we will not distinguish between the two unless strictly necessary.

510 3 Methods for the deterministic Unit Commitment

511 We now proceed with a survey of solution methods for (the deterministic) UC. Our choice to first focus
 512 on the case where the several forms of uncertainty arising in UC (cf. §2.1) are neglected is justified by
 513 the following facts:

- 514 – UC already being a rather difficult problem in practice, most work has been carried out in the
 515 deterministic setting;
- 516 – uncertainty can be taken into account through various “engineering rules”: for instance, spinning
 517 reserves allow to account for uncertainty on load, tweaking reservoir volumes might allow to account
 518 for uncertainty on inflows, and so on;
- 519 – methods for solving the deterministic UC are bound to provide essential knowledge when dealing
 520 with UUC.

As discussed in Section 2, UC is not one specific problem but rather a large family of problems exhibiting common features. Since the set of constraints dealt with in the UC literature varies from one source to another, we define what we will call a *basic Unit Commitment problem* (bUC) which roughly covers the most common problem type; through the use of tables we will then highlight which sources consider additional constraints. A bUC is a model containing the following constraints:

1. offer-demand equilibrium;
2. minimum up or down time;
3. spinning reserve;
4. generation capacities.

The UC literature review [349], of which [290] is essentially an update adding heuristic approaches, generally classify UC methodology in roughly eight classes. We will essentially keep this distinction, but regroup all heuristic approaches in “Meta-Heuristics”, thus leading us to a classification in:

1. Dynamic Programming;
2. MILP approaches;
3. Decomposition approaches;
4. (Meta-)Heuristics approaches.

We will also add some of the early UC approaches in the Heuristic class such as priority listing. However, we will not delve much on that class of approaches, since the recent surveys [127, 337] mainly focus on these, while providing little (or no) details on approaches based on mathematical programming techniques, that are instead crucial for us in view of the extension to the UUC case.

3.1 Dynamic Programming

Dynamic Programming (DP, see e.g. [33, 49, 50]) is one of the classical approaches for UC. As discussed below, it is nowadays mostly used for solving *subproblems* of UC, often in relation with Lagrangian-based decomposition methods (cf. §3.3); however, attempts have been made to solve the problem as a whole. There have been several suggestions to overcome the *curse of dimensionality* that DP is known to suffer from; we can name combinations of DP and Priority Listing (DP-PL) [189, 361], Sequential Combination (DP-SC) [293], Truncated Combination (DP-TC) [292], Sequential/Truncated Combination (DP-STC) (the integration of the two aforesaid methods) [293], variable window truncated DP [287], approximated DP [104] or even some heuristics such as the use of neural network [287] or artificial intelligence techniques [392]. The multi-pass DP approach [124, 416] consists of applying DP iteratively, wherein in each iteration the discretization of the state space, time space and controls are refined around the previously obtained coarse solution; usually, this is applied to ED, i.e., once commitment decisions have been fixed. In [293] three of the aforesaid methods, DP-PL, DP-SC, and DP-STC are compared against a priority list method on a system with 96 thermal units, showing that the DP-related approaches are preferable to the latter in terms of time and performance. The recent [359] performs a similar study on a bUC with 10 thermal units, but only DP approaches are investigated.

Despite its limited success as a technique for solving UC, DP is important because of its role in dealing with sub-problems in decomposition schemes like Lagrangian relaxation. These typically relax the constraints linking different unit together, so that one is left with single-Unit Commitment (1UC) problems, i.e., self-scheduling ones where the unit only reacts to price signals. In the “basic” case of time-independent startup costs 1UC can be solved in linear time on the size of \mathcal{T} . When dealing with time-dependent startup costs instead, this cost becomes quadratic [29, 427]. However, this requires that the optimal production decisions p_t^i can be independently set for each time instant if the corresponding commitment decision u_t^i is fixed, which is true in bUC but not if ramp rate constraints are present. It is possible to discretize power variables and keep using DP [32], but the approach is far less efficient and the determined solution is not guaranteed to be feasible. An efficient DP approach for the case of ramp rate

constraints and time-dependent startup costs has been developed in [126] under the assumption that the power production cost is piecewise linear. This has been later extended in [142] for general convex cost functions; under mild conditions (satisfied e.g., in the standard quadratic case), this procedure has cubic cost in the size of \mathcal{T} . DP has also been used to address hydro valley subproblems in [360] where a three stage procedure is used: first an expert system is used to select desirable solutions, then a DP approach is used on a plant by plant basis, and a final network optimization step resolves the links between the reservoirs. In [334] expert systems and DP are also coupled in order to solve UC. We also mention the uses of expert systems in [253].

Most often DP approaches are applied to bUC, but other constraints have been considered such as multi-area, fuel constraint, ramp rates, emission constraints, and hydro-thermal systems. We refer to Table 1 for a complete list.

Table 1 Sources using Dynamic Programming

Basic UC			Additional UC constraints										
			Must Run/Off	Fixed Generation	Crew Constr.	Ramp Rate	Operating Reserve	Maintenance	Hydro-Thermal	Fuel Const.	Emission		
[292]	[293]	[287]	[292]	[288]	[292]	[142]	[143]	[360]	[253]	[143]	[360]	[4]	[190]
[288]	[142]	[143]				[126]	[253]						
[126]	[360]	[334]				[392]							
[253]	[359]	[32]											

3.2 Integer and Mixed Integer Linear Programming

3.2.1 Early use: exhaustive enumeration

As its name implies, this approach focuses on a complete enumeration of the solution space in order to select the solution with the least cost. bUC is addressed in [172, 204], while in [172] the cost function considers penalties for loss of load and over production. In [204] a set of 12 thermal units on a two hour basis is scheduled. In [172] a problem with two groups, each of which has 5 thermal units is analyzed. This traditional approach obviously lacks scalability to large-scale systems. However, some enumeration may find its way into hybrid approaches such as decomposition methods under specific circumstances, like in [132] where enumeration is used in some of the subproblems in a decomposed hydro valley system.

3.2.2 Modern use of MILP techniques

With the rise of very efficient MILP solvers, MILP formulations of UC have become common. In general, their efficiency heavily depends on the amount of modeling detail that is integrated in the problem. Early applications of MILP can be found in [88, 151, 263], and in [88] it is stated that the model could be extended to allow for probabilistic reserve constraints. Hydro-thermal UC is considered in [114, 304, 348] where constraints regarding hydro units such as flow equations, storage level of reservoirs, pump storage and min and max of outflow of each reservoir are incorporated in the model.

Some specific constraints such as the number of starts in a day or particular cost functions with integrated banking costs can be found in [212, 376]. In [212] the authors combine Lagrangian relaxation (e.g., [262]) with a B&B procedure in order to derive valid bounds to improve the branching procedure. The upper bound is derived by setting up a dynamic priority list in order to derive feasible solutions of the UC and hence provide upper bounds. It is reported that a 250 unit UC was solved up to 1% of optimality in less than half an hour, a significant feat for the time. A similar approach is investigated in [299], where a heuristic approach using, among things, temporal aggregation is used to produce a good quality integer feasible solution to warm-start a B&B procedure.

While MILP is a powerful modeling tool, its main drawback is that it may scale poorly when the number of units increases or when additional modeling detail is integrated. To overcome this problem it

604 has been combined with methods such as DP [61], logic programming [191] and Quadratic Programming
 605 (QP) [345]. In [345] a hydro-thermal UC with various constraints is solved; a customized B&B procedure
 606 is developed wherein binary variables are branched upon according to their difference from bounds.
 607 The approach does not require any decomposition method, and it is reported to reduce solution time
 608 significantly in comparison to other methods. The paper builds upon [147], where a six-step solution is
 609 proposed to solve large-scale UC; the algorithm is reported to be capable of solving security-constrained
 610 problems with 169, 676 and 2709 thermal units in 27s, 82s and 8 minutes, respectively. This so-called
 611 Fast-Security Constraint Unit Commitment problem (F-SCUC) method is based on an ad-hoc way of
 612 fixing binary variables and gradually unlock them if needed, using Benders-type cuts to this effect.
 613 However, in [143] it is reported that MILP models where the objective function is piecewise-linearly
 614 approximated are much more effective than the direct use of MIQP models, at least for one specific
 615 choice and version of the general-purpose MIQP solver. In [145] MILP and Lagrangian methods are
 616 combined, solving problems with up to 200 thermal units and 100 hydro units in a few minutes if the
 617 desired accuracy is set appropriately.

618 Systems with a significant fraction of hydro generation require a specific mention due to a notable char-
 619 acteristic: the relationship between the power that can be generated and the level of the downstream
 620 reservoir (head-to-generated-power function), that can be highly nonlinear [76], and in particular noncon-
 621 vex. This can be tackled by either trying to find convex formulations for significant special cases [417],
 622 developing ad-hoc approximations that make the problem easier to solve [77], or using the modeling
 623 features of MILP to represent this (and other nonconvex) feature(s) of the generating units [83, 306].
 624 However, developing a good approximation of the true behavior of the function is rather complex be-
 625 cause it depends on both the head value of the reservoir and the water flow. MILP models for accurately
 626 representing this dependency have been presented in [197], and more advanced ones in [63] using ideas
 627 from [98]; while they are shown to significantly improve the quality of the generated schedules, this
 628 feature makes UC markedly more complex to solve.

629 3.2.3 Recent trends in MILP techniques

630 Recently, MIP (and in particular MILP) models have attracted a renewed attention due to a number
 631 of factors. Perhaps the most relevant is the fact that MILP solvers have significantly increased their
 632 performances, so that more and more UC formulations can be solved by MILP models with reasonable
 633 accuracy in running times compatible with actual operational use [75]. Furthermore, selected nonlinear
 634 features—in particular convex quadratic objective functions and their generalization, i.e., Second-Order
 635 Cone Constraints—are nowadays efficiently integrated in many solvers, allowing to better represent some
 636 of the features of the physical system. This is especially interesting because MIP models are much easier
 637 to modify than custom-made solution algorithms, which—in principle—allow to quickly adapt the model
 638 to the changing needs of the decision-makers. However, it has to be remarked that each modification
 639 to the model incurs a serious risk of making the problems much more difficult to solve. Two somewhat
 640 opposite trends have recently shown up. On one side, *tighter formulations* are developed that allow to
 641 more efficiently solve a given UC problem because the continuous relaxation of the model provides better
 642 lower bounds. On the other hand, *more accurate models* are developed which better reflect the real-world
 643 behavior of the generating units and all the operational flexibility they possess (cf. e.g. [188, 236, 245]),
 644 thereby helping to produce better operational decisions in practice.

645 On the first stream, the research has focused on finding better representations of significant fragments
 646 of UC formulations. For instance, [257, 282] develop better representations of the polyhedra describing
 647 minimum up- and down-time constraints and ramping constraints, whereas [144, 196, 408] focus on better
 648 piecewise-linear reformulations of the nonlinear (quadratic) power cost function of thermal units. Both
 649 approaches (that can be easily combined) have been shown to increase the efficiency of the MILP solver
 650 for a fixed level of modeling detail.

651 The second stream rather aims at improving the accuracy of the models in representing the real-world
 652 operating constraints of units, that are often rather crudely approximated in standard UC formulations.
 653 For hydro units this for instance concerns technical constraints [83] and the already discussed water-

654 to-produced-energy function, with its dependency from the water head of the downstream reservoir
 655 [63, 132, 306]. For thermal units, improvements in the model comprise the correct evaluation of the
 656 power contribution of the start-up and shut-down power trajectories (when a unit is producing but no
 657 modulation is possible) [17], which may make the model significantly more difficult unless appropriate
 658 techniques are used [258], or a clearer distinction between the produced energy and the power trajectory
 659 of the units [150, 259].

660 In the OTS context (cf. § 2.7), special care must be given when modeling the Kirchhoff laws, as this leads
 661 to logic constraints that, in MILP models, are typically transformed into “Big-M” (hence, weak) linear
 662 constraints. Moreover, severe symmetry issues [283] must be faced [243, 285], as these can significantly
 663 degrade the performances of the B&B approach. All these difficulties, not shared by UC with DC
 664 or AC network constraints, require a nontrivial extension of the “classic” MILP UC models. Many
 665 approaches use off-the-shelf B&B solvers, while possibly reducing the search space of the OTS binary
 666 variables [233, 284, 327] and using tight formulations for the thermal units constraints. All the references
 667 use classic quadratic cost functions; one exception can be found in [243], where a direct MILP approach
 668 is combined with a perspective cuts approximation [144] and a special perturbation of the cost function
 669 that successfully breaks (part of the) symmetries. Together with heuristic branching priorities that give
 670 precedence to the thermal UC status variables, this is shown to be much better than using a classic
 671 quadratic function, with or without perturbations, for solving the IEEE 118 test case.

Table 2 Sources using MILP approaches

Basic UC	Additional UC constraints										
	Must Run/Off	Trans -OTS	Modulation	Starts	Hot/Cold Starts	Ramp Rate	Hydro-Thermal	Water-head	Thermal-Stress	Fuel	Emission
[114, 151, 263] [61, 115, 376] [171, 304, 348] [88, 191, 212] [245, 345]	[114] [144] [145]	[134, 304] [236, 243] [176, 177] [298, 327] [280, 285] [233, 284] [207, 232] [174, 175] [420]	[114]	[376]	[212]	[191, 345] [75, 145] [236, 282] [144, 257] [17, 196] [150, 258] [150, 259]	[345, 348] [114, 304] [145, 274] [144]	[306, 417] [63, 83] [132]	[228]	[236]	[236]

672 3.3 Lagrangian and Benders Decomposition

673 UC possesses several forms of structure that can be algorithmically exploited; the most obvious one
 674 is that (complex) units are usually coupled through demand and reserve requirements (the set X_2 in
 675 (1)). Since these constraints are usually in limited number and “simple”, Lagrangian Decomposition (or
 676 Relaxation, LR) [140, 167, 220] is an attractive approach and has been widely used. It is based on relaxing
 677 these coupling constraints by moving them in the objective function, weighted by appropriate *Lagrangian*
 678 *multipliers*, so that the relaxed problem then naturally decomposes into independent subproblems for
 679 each individual unit (1UC); for an arbitrary set of Lagrangian multipliers, the solution of all the 1UCs
 680 provides a lower bound on the optimal value of (1). Moreover the mapping (called the dual function,
 681 or Lagrangian function) assigning this optimal value to a given set of Lagrangian multipliers is concave;
 682 maximizing it, i.e., finding the best possible lower bound, is therefore a convex optimization problem for
 683 which efficient algorithms exists.

684 Two technical points are crucial when developing a LR approach:

- 685 – how the maximization of the Lagrangian function, i.e., the solution of the *Lagrangian Dual* (LD), is
 686 performed;
- 687 – since (1) is in general nonconvex the approach cannot be expected to provide an optimal (or even
 688 feasible) solution, so methods to recover one have to be developed.

689 Regarding the first point, one can rely on the available well-developed theory concerning minimiza-
 690 tion of convex nondifferentiable functions. Standard approaches of this kind are *subgradient meth-*

691 *ods* [100,270,308] and the *cutting plane method* (CP) [203], also known as the *Dantzig-Wolfe decomposi-*
 692 *tion method* [101]. Early examples of the use of subgradient methods in UC are [29,47,135,248,262,427],
 693 possibly with modifications such as successive approximation techniques [87] or variable metric ap-
 694 proaches [12]. An early example of the use of CP is [2]. The two approaches are rather different: subgra-
 695 dient methods use very simple rules to compute the next dual iterate, whereas CP uses (possibly costly)
 696 Linear Programming (LP) problems for the same task, although hybrid versions have been devised [369].
 697 This is necessary in practice because both approaches have convergence issues, for different reasons: sub-
 698 gradient methods lack an effective stopping criterion, whereas CP tends to be unstable and converge
 699 slowly. This is why variants of CP have been devised, e.g., using Interior Point ideas to provide some
 700 stabilizing effect [118]; for an application to UC see [244]. In [332] the KKT conditions of the Lagrange
 701 function are used in order to update the Lagrange multipliers and improve on subgradient approaches.
 702 In [319] CP is stabilized by a trust region. The latter turns out to be a special case of the most effective
 703 family of approaches capable of dealing with this kind of problems, that is, (generalized [139]) *Bundle*
 704 *methods* [219,402]. These can be seen as a “mix” between subgradient and CP [22] which inherits the
 705 best properties of both [68]. Several variants of Bundle approaches exist, see e.g. [18,221,222]; a recent
 706 development that is particularly useful for UC is that of methods that allow the inexact solution of the
 707 Lagrangian relaxation [106,107,206]. This feature is of particular interest if operational considerations
 708 impose strong restrictions on the solution times for the subproblems. For early application of Bundle
 709 methods to UC see e.g., [64,65,128,159,223,242,421].

710 Regarding the second point, one important property of LDs of non-convex programs is that, while
 711 they cannot be guaranteed to solve the original problem, they indeed solve a “convexified version” of
 712 it [140,220]. In practice, this typically corresponds to a solution $\tilde{x} = (\tilde{p}, \tilde{u})$ to (1) that is feasible for all
 713 constraints except the integrality ones. That is, rather than feasible commitment decisions $u_t^i \in \{0,1\}$ one
 714 obtains *pseudo-schedules* $\tilde{u}_t^i \in [0,1]$ that satisfy the constraints with the production decisions \tilde{p} . Such
 715 a solution can be obtained basically for free by (appropriately instrumented versions of) subgradient
 716 methods [10,28] and all other algorithms, most notably Bundle ones [128]. The pseudo-schedule \tilde{x} can
 717 for instance be heuristically interpreted as the *probability* that unit i be on at instant t , and then be
 718 used in this guise to devise *primal recovery* approaches to attain feasible solutions of (1), either by
 719 appropriately modifying the objective function [99,119] or by a heuristic search phase that exploits both
 720 \tilde{x} and the integer solutions produced by the LR [31,143,333].

721 Along with early papers which address the bUC [47,135,248,262], we mention papers which address large-
 722 scale UC [47,248]. The authors of [248] are among the first who tried to use LR to obtain a solution,
 723 and not just to obtain lower bounds for B&B procedures, solving a problem of 172 units. In [212] the
 724 duality gap problem is tackled by approximating the dual problem with a twice-differentiable mapping
 725 which is then maximized by using a constrained Newton’s method, after which a heuristic is used to
 726 recover a nearly optimal primal solution; a 200 units UC is solved in about 10 to 12 minutes. In a
 727 subsequent work [348], a three-stage approach is proposed to deal with a—for the time—large-scale
 728 hydro-thermal system (100 thermal units and 6 hydro ones). The first stage is based on LR, with the
 729 thermal 1UCs solved using DP, while the hydro subproblems are solved by using a penalty multipliers
 730 method [208] and a specially tailored Newton’s method. A “unit decommitment” method is suggested
 731 in [225,373] where all units are considered online over all \mathcal{T} and then, using the results of the LR, units
 732 are decommitted one at a time. This method aims at providing feasible primal solutions first, whereas
 733 most LR approaches would aim at optimality first. Further references using LR are [129,164,335,336],
 734 which consider specific dedicated approaches in order to tackle the subproblems, elementary ways of
 735 updating the dual and heuristics to recover a primal feasible solution. In [162] the units cost functions
 736 are modified in order to reduce the oscillating behavior of subgradient approaches. In [159] the authors
 737 compare a primal MIP based approach with a LR-based approach: Bundle methods are used in order to
 738 solve the LD and two Lagrangian heuristics are investigated for primal recovery. The first one searches
 739 for time steps where demand constraints are most violated and employs a strategy proposed in [427] for
 740 changing the commitment variables, while the second one exploits nearly optimal Lagrange multipliers
 741 for fixing commitment decisions. In order to recover primal feasibility, both heuristics are followed by
 742 solving an ED, wherein the commitment variables are fixed; this LR-based method is shown to be capable
 743 of handling larger and more complex instances. In [366] the Lagrangian heuristic consists of formulating

744 a MIP that mixes solutions provided by the dual iterations, selecting the production schedule of a
 745 specific unit among the primal solutions generated by the LD phase in such a way as to minimize
 746 overall cost and satisfy (the dualized) demand constraints. The resulting MIP is then reformulated in
 747 order to allow for an efficient solution. A similar idea is exploited in [237], where the MIP is solved by
 748 using Genetic Algorithms. In [128] the dual multipliers defining the pseudo-schedule are interpreted as
 749 probabilities for randomly selecting commitment decisions after a LD phase; four derived Lagrangian
 750 heuristics are investigated. In [34] a two step procedure is proposed, consisting of a LD phase followed
 751 by an Augmented Lagrangian (AL) phase for primal recovery. The AL term is linearized in an ad-hoc
 752 way and its penalty slowly sent to infinity. Bundle methods, CP and sub-gradient methods are compared
 753 for solving the LD phase; it is shown that Bundle methods outperform alternative approaches. Finally,
 754 in [64] Lagrangian approaches are compared with Tabu Search heuristics, and an improved primal phase
 755 is proposed in [65]. The approach is later extended to the free-market regime [66] and to the handling
 756 of ramping constraints [143] via the use of the specialized DP procedure of [142]. An hybrid version also
 757 using MILP techniques is presented in [145].

758 LR can be used to deal with ramp rate constraints, fuel related constraints and emission constraints
 759 [12, 87, 369, 413, 427] by simply relaxing them (in Lagrangian fashion). Similarly, LR can be employed to
 760 further decompose subproblems, in particular hydro ones; these ideas are explored in [131, 132, 165, 272,
 761 364, 365]. More specifically, the authors of [165] consider the LD related to the bounds on the reservoir
 762 levels in the hydro subproblem, which effectively decomposes the problem in smaller MILPs that can
 763 then be readily dealt with, through the use of DP in this specific case. The LD is optimized using a
 764 subgradient approach, and heuristics are used to recover a primal feasible solution. A similar approach
 765 is used in [272], where hydro units have discrete commitment decisions much like thermal ones. These
 766 constraints are then relaxed in a Lagrangian way, resulting in continuous network flow subproblems and
 767 a pure integer problem. In [132], *Lagrangian decomposition* [168] is used to deal with forbidden zones
 768 in complex hydro units. The idea is to use LR to decompose hydro valley subproblems further into
 769 two parts: the first part deals with the flow constraints and basically leads to a simple LP, while the
 770 second part deals with the water-head effect and other combinatorial constraints and requires a specific
 771 NLP approach (an SQP-based method and partial exhaustive enumeration). Two dual formulations are
 772 considered which differ from each other in that in the second one the NLP problem is further decomposed
 773 through the use of auxiliary variables. The model is extended to consider network constraints in [364],
 774 and different relaxation schemes are explored in [365] and [131]; in particular, the latter compares
 775 Lagrangian relaxation and Lagrangian decomposition. In [413] a system with 70 thermal and 7 hydro
 776 units is addressed. Ramp rate constraints are also dualized, and the DP approach of [163] is used to
 777 optimize the thermal units, while a merit order allocation is employed for the hydro subproblem. In [427]
 778 a three stage approach is proposed based on first solving the LR, then finding a feasible solution for
 779 reserve requirements and finally solving an ED. In [274] a hydro-thermal system with a fairly realistic
 780 model for hydro generation is considered that comprises *forbidden zones* (cf. §2.4) and the water head
 781 effect. The offer-demand equilibrium constraints and reservoir balance equations are dualized, and the
 782 LD is maximized with a subgradient approach, with a heuristic step fixing the discrete hydro variables
 783 to recover a primal feasible hydro solution. In [2] some transmission constraints are considered. In [228]
 784 an alternative to ramping rate constraints in the model for thermal units, a so-called stress effect,
 785 is proposed. Coupling offer-demand equilibrium and reserve requirement constraints are dualized; the
 786 corresponding LD is maximized using a subgradient approach, where the thermal subproblems are solved
 787 using Simulated Annealing techniques. In [148] a ramp rate, fuel and emission constrained UC is solved.

Table 3 Sources using Lagrangian Relaxation

Basic UC	Additional UC constraints						
	Must Run/Off	Fuel Constr.	Ramp Rate	Suppl. Reserve	Hydro-Thermal	Emission	Transmission
[2, 12, 87, 248, 262] [135, 274, 369, 413, 427] [64, 126, 128, 244, 348] [47, 148, 228]	[413, 427] [145]	[12, 369] [87, 148]	[87, 148, 413] [143, 145] [65, 66] [11, 228]	[2, 87]	[12, 365, 413] [66, 143, 145] [65, 274, 348] [11, 131, 132]	[148, 158, 209]	[2, 364]

788 A different decomposition approach is the classic one due to Benders [44] [62, Chapter 11.1], which
 789 rather focuses on *complicating variables* that, once fixed, allow to separate the problem into independent
 790 (and, hopefully, easy) ones. Application of Benders' decomposition to UC is fairly recent. In [231, 407]
 791 techniques for improving the Benders' cuts production are described. In [146] a conceptual and nu-
 792 merical comparison is made, in the context of the security constrained UC, between LR and MILP
 793 approaches (cf. §3.2) for the solution of *master* problem of Benders' decomposition. For the subprob-
 794 lems, involving the network constraints, the authors compare Benders' cuts and linear sensitivity factor
 795 (LSF) approaches.

796 3.4 Augmented Lagrangian Relaxation

797 One major downside of LR approaches is the difficulty in recovering a primal feasible solution. The use of
 798 the Augmented Lagrangian (AL) method, whereby a quadratic penalization of the relaxed constraints is
 799 added to the objective function alongside the linear penalization typical of standard LR, is known to be
 800 a potential solution to this issue. Yet, because (1) is nonconvex it should be expected that in general the
 801 AL approach leads to a local optimizer [157, 240]. Furthermore, the AL relaxation is no longer separable
 802 into an independent subproblem for each unit, and therefore it is significantly more difficult to solve
 803 (in practice, as difficult as UC itself). This calls for some further approach to simplify the relaxation;
 804 in [31, 414] the use of the *auxiliary problem principle* [89, 90] is suggested. The classic theory of the
 805 auxiliary problem principle requires restrictive assumptions such as convexity and regularity, which do
 806 not hold in practice; some recent advances have been made in the non-convex setting [19, 317, 374]. In [35]
 807 an alternative decomposition scheme based on block coordinate descent (e.g. [48, 328]) is proposed and
 808 it is found to be more efficient. The recent [249] includes in the UC formulation a DC network model
 809 and bilateral contracts defining the nodal injections. The AL of the coupling constraints is formed and
 810 then linearized in an ad-hoc way, while Bundle methods are employed for updating the dual multipliers.
 811 Environmental constraints [399] and network transmission constraints [35, 399] have also been tackled
 812 with the AL approach. A common way to deal with additional constraints is variable duplication [153].

Table 4 Sources using Augmented Lagrangian Approaches

Basic UC	Additional UC constraints					
	Modulation	Startup/shutdown curves	Transmission	Ramp Rate	Environ. Const.	Hydro-Thermal
[25, 31, 35, 399]	[31]	[31]	[25, 35, 399]	[25, 31]	[399]	[25, 31]

813 3.5 (Meta-)Heuristics

814 3.5.1 Operator rule based: Priority Listing

815 This method defines a list of units which should logically be scheduled prior to other units, with merit
 816 order scheduling being a special case. Priority listing was first employed on bUC in [26], where units
 817 are listed according to their performance and the cost they yield (comprising maintenance costs). Must-
 818 on/must-off and crew constraint have been added in [215], and a limit on the number of starts is included
 819 in [216] through the use of a commitment utilization factor, which is claimed to provide a better list.
 820 While the former two papers and [5] address bUC, there has been an endeavour to integrate other factors
 821 such as multi-area constraints [217] and hydro-thermal systems [200] for large-scale UC. In the latter
 822 paper a two-step heuristic procedure is used to solve a UC with 100 units: the first step uses rules from
 823 real-world schedules (possibly enhanced by the use of UC software) to set up a priority list consisting
 824 of feasible production schedules, while the second step optimizes locally around the current solution. A
 825 very similar approach is investigated in [5].

Table 5 Sources using Priority Listing

Basic UC	Additional UC constraints					
	No.Units Started	Crew Const.	Must run/Off	Multi-Area	Hydro-Thermal	No. Starts / Shutdowns
[5, 26, 200, 215–217]	[200]	[215]	[215, 217]	[217]	[200]	[216]

3.5.2 Guided Random Exploration

Since solving the UC (1) to optimality is quite difficult, many heuristic approaches such as Taboo search, Simulated Annealing, Augmented Lagrange Hopfield Networks, Nature Inspired (e.g., particle swarms, frog leaping, ...) and Genetic Algorithms have also been employed. We refer to [127,337] for a discussion of those approaches, and in this paper we by no means attempt to give a full overview of this subfield. This is because heuristic approaches like these are typically difficult to adapt to the Uncertain UC case, which is the main focus of this survey, unless they are at least partly based on mathematical programming techniques. We therefore concentrate mostly on “hybrid” approaches that use the latter at least to a certain degree. For instance, in [237] genes are feasible schedules produced by a LR-based scheme: the genetic algorithm then mixes the solutions up to form new feasible schedules in order to hopefully produce a solution that better meets the demand constraints. In [428] the authors solve a 100 thermal unit system by using Simulated Annealing and report that their approach outperforms a B&B procedure, but fails to outperform a LR approach (although in the later [64] Taboo search has been reported to be more competitive with LR). In [120,201] Evolutionary Programming is applied to adjust the solution provided by a LR approach. In [241] a neural network approach is coupled to LR in order to optimize a system with up to 60 units: the thermal subproblems are optimized using a neuron-based DP algorithm.

In general, these approaches are not considered particularly competitive for UC; for instance, [368] states that Simulated Annealing and Evolutionary Programming attempts have been unsuccessful. Also, usually these approaches deal with bUC, with only a few sources considering ramp rate, crew, maintenance or multi-area constraints, and hydro-thermal systems being very rarely dealt with. The likely reason is that purely combinatorial heuristics are best apt at problems that exhibit a predominant and relatively “simple” combinatorial structure to which the various elements of the heuristic (neighborhood(s) structure in Simulated Annealing, Taboo list and aspiration criteria in Taboo search, mutation and crossover operators in genetic algorithms, ...) can be specifically tailored. UC is a fundamentally *mixed* combinatorial *and* continuous program, since both the commitment and the dispatch have to be provided. Furthermore, UC has several different combinatorial structures, especially when “complex” constraints have to be dealt with. Therefore, on the outset UC is best approached with mathematical programming techniques.

Table 6 provides a (very partial) overview of heuristic approaches:

Table 6 Sources using (Meta-)Heuristic Approaches

Approach	Basic UC	Additional UC constraints					
		Ramp Rate	Crew Constr.	Maintenance	Multi-Area Const.	Hydro-Thermal	Derating
Simul. Annealing	[8, 358, 428] [246]	[358]	[8, 246, 428]	[428]			
Tabu Search	[246, 260, 387] [64, 230] [247, 314]		[246]			[247]	[246]
Neural Network	[339, 343, 391] [1, 344, 392] [113, 229, 266] [241]	[1, 343] [113, 392]	[266]			[391]	
Genetic Algorithm	[363, 403, 404] [86, 378, 415] [313, 315, 350] [120, 201, 415] [102, 237]	[350, 403] [313]			[86, 315]		
Nature Inspired	[81, 82, 152]	[81, 82, 152]			[82]		

856 4 Methods for the Uncertain Unit Commitment

857 The complex nature of UC, due to its numerous technical constraints, forces the schedule to be deter-
858 mined quite ahead of time and consequently be given to the TSO one day in advance. This allows for
859 uncertainty to have an important impact on the system. Furthermore, intra-daily optimization processes
860 and communication between the TSO and the GENCOs allow for recourse decisions. Thus, dealing with
861 uncertainty has always been necessary in UC. We now discuss the approaches that have been proposed
862 in the literature. To the best of our knowledge, this has never been done before specifically for the UC.
863 The chapter [390] provides a general overview of the ways in which uncertainty arises in Energy Man-
864 agement, but it is mainly focused on mid- and long-term problems, UC being only briefly addressed.
865 Analogously, [91] offers a general survey on uncertainty issues in Energy Optimization, without a spe-
866 cific focus on UC. The chapter [325] offers a general overview of properties of stochastic optimization
867 problems and briefly provides some links to stochastic UC problems. The essential references used in
868 these sources will be discussed below.

869 4.1 Dealing with Uncertainty in UC

870 In most traditional approaches, load uncertainty is dealt with by computing the schedule corresponding
871 to the worst scenario, i.e., typically that of peak demand in each period. This choice systematically
872 overestimates demand and incurs the risk that significant ramp-down of the production is needed when
873 the actual demand proves to be substantially smaller than the forecasted one, which can cause feasibility
874 issues due to technical constraints like *ramp-down* ones (cf. §2.3). Another common approach has been to
875 use spinning reserve constraints (cf. §2.6) [9, 57, 138, 160, 409]; the advantage is that this protects against
876 some degree of uncertainty while keeping the deterministic formulation. In general, the deterministic
877 constraints can be “tweaked” heuristically in order to deal with uncertainty. For instance, in order to
878 ensure that the solution can survive a certain degree of variability in the data we can underestimate
879 the amount of water in a hydro reservoir and/or impose stricter ramp-rate constraints than justified by
880 technical aspects. Obviously, this may result in a loss of optimality or control over feasibility. Worse, one
881 may lose control over where the approximations have been made.

882 In order to overcome these weaknesses, methods where uncertainty is directly modeled have been in-
883 vestigated. These comprise Stochastic Optimization (scenario tree), Robust Optimization, and Chance-
884 Constrained Optimization.

885 4.1.1 Dealing with uncertainty in the model

886 *4.1.1.1 Stochastic optimization.* Scenario tree based approaches (from now on denoted as SO, i.e.,
887 Stochastic Optimization) have been the subject of intense research in the last two decades; see e.g. [309,
888 Chapter 13] [59, 202, 235, 330, 331] among the many other general references. Their use in the UC con-
889 text has been considered e.g. in [74, 289, 367, 405, 411]. The key advantage of using scenario trees is
890 that uncertainty is assumed to be known in each node of the tree. Since moreover uncertainty is now
891 discretized on the tree, essentially this amounts to solving a deterministic UC of very large scale. The
892 authors of [375] demonstrate the interest of SO over deterministic optimization using such a direct re-
893 formulation. According to [52], SO methods have two major drawbacks. First, obtaining an accurate
894 probability distribution can be difficult, i.e., setting up an accurate tree is hard. Indeed, while generat-
895 ing scenarios for each individual uncertainty factor may be relatively straightforward, combining these
896 to form a tree structure is not easy. Second, these solutions provide only probabilistic guarantees. The
897 first difficulty can be partially tackled by the approaches considered in [121, 123, 178–180], that provide
898 a systematic approach for generating manageable trees. Classical approaches (e.g. [367]) to form a tree
899 are those that start out with a set of scenarios and progressively regroup similar scenarios to form the
900 nodes, in each of which a representing scenario is selected. The use of physical models for generating
901 uncertainty (e.g. [95]) could also help improve the realism of the underlying scenario tree. The second

902 difficulty can be tackled by using a hybrid approach that also considers spinning reserve requirements on
 903 the scenario tree [326, 409], which can be used to account for events not modeled in the tree. We mention
 904 in passing that similar techniques can also be applied to longer-term problems, such as the management
 905 of an hydro reservoirs, that although not strictly pertinent to this paper are clearly strongly related. For
 906 a recent instance, a specialized stochastic dual DP algorithm is proposed in [170].

907 *4.1.1.2 Robust optimization.* In order to be less demanding on the representation of uncertainty, Robust
 908 Optimization (RO) uses the notion of *uncertainty set*, which basically reunites the adverse events against
 909 which we wish to protect ourselves. For a comprehensive introduction to robust optimization we refer
 910 to [38, 51]; other important references are [40–42, 53, 54, 154, 155]. RO approaches might lead to a sub-
 911 stantially higher costs of the proposed solution—a too high “price of robustness” [54]—w.r.t. SO ones
 912 when distributions of the uncertainty are sufficiently well characterized. This is mainly because RO pro-
 913 tects against each event in the specified uncertainty set regardless of its probability, and therefore may
 914 have to account for extremely unlikely events. Several RO approaches have parameters (e.g., “budget
 915 of uncertainty”) that can be used to adjust the degree of protection offered by the model [53, 84, 268];
 916 yet, in general tuning these parameters is far from trivial. To reduce the price of robustness associ-
 917 ated with classical ellipsoidal and Γ -robustness uncertainty sets proposed in [40, 54, 155], subsequent
 918 studies have investigated alternative *soft* and *light* robustness models [37, 133]. Recently, *multiband ro-*
 919 *bustness* [69, 70], has been proposed as a generalization of Γ -robustness that can support an improved
 920 and stratified representation of uncertainty and a reduction in conservatism, while maintaining the com-
 921 putational tractability and accessibility of Γ -robustness.

922 *4.1.1.3 Chance-Constrained Optimization.* Chance-Constrained Optimization provides an attractive way
 923 to select the trade-off between cost and robustness, using a notion—the probability of the selected
 924 solution to be feasible—that is easy for the decision-maker to understand and manage. We refer to
 925 [110, 309, 310] for a modern introduction to probabilistic programming. In [381] the potentials for energy
 926 management applications, such as UC, are evaluated. However, a drawback of CCO is that probabilistic
 927 constraints can be nonconvex and hard to evaluate, thus making these approaches potentially computa-
 928 tionally demanding.

929 *4.1.1.4 The link between RO and CCO.* There actually is an important link between RO and CCO.
 930 Indeed, an intuitively appealing idea is to select the uncertainty set in such a way as to enforce a
 931 probabilistic constraint, so that the solutions produced by the RO approach are comparable with those
 932 produced by the CCO one. More generally, one may aim at replacing the probabilistic constraint with a
 933 convex, albeit possibly more restrictive, constraint. There are various ways of doing this (e.g. [43, 268]),
 934 often referred to as “safe-tractable approximation approaches” (a somewhat unfortunate terminology
 935 implicitly assuming that all CCO problems are intractable, which is not the case). Frequently, such convex
 936 outer approximations of the CCO-feasible set are derived by using individual probabilistic constraints,
 937 i.e., constraints that require that each individual inequality in the constraints system holds with high
 938 enough probability (e.g. [84]). Besides using a (not necessarily very tight) approximation, this approach
 939 gives little control over the *joint* violation of the constraints, although it does have the advantage that
 940 convexity makes the corresponding problems easier to solve. We refer to [380, 382] for examples showing
 941 that individual probabilistic constraints may lead to an arbitrary number of violated constraints. We also
 942 refer to [27, 166] for various other alternatives of building uncertainty sets. The scenario approximation
 943 approach (e.g. [71, 267, 269]) can be seen as a special case of RO with a discrete uncertainty set that
 944 arose by drawing random samples from the underlying distribution.

945 *4.1.2 Modelling and solution choices*

946 *4.1.2.1 The choice of recourse decisions.* A crucial decision in all two-stage (or multi-stage) models, be
 947 they SO, RO or CCO, is which variables represent “here and now decisions” (first stage), to be taken

948 before the uncertainty is revealed, and which represent “recourse actions” (second or later stages) that
 949 can change when the uncertain parameters are revealed. In multi-stage models a whole chain of decisions
 950 and observation of uncertainty needs to be worked out properly. This decision-observation chain may
 951 end with the observation of a last random realization offering no recourse actions. This could give rise
 952 to the need to consider multi-stage RO (CCO) approaches. When recourse is incomplete (i.e., can not
 953 guarantee feasibility of later stages regardless of the random realizations) such a need may also arise.

954 In general, recourse formulations aim at minimizing the total cost of the here and now decisions and
 955 the expected cost of the possible recourse actions. These problems are typically very challenging from
 956 both the computational and theoretical point of view, especially if recourse actions are integer-valued
 957 (or otherwise belong to a non-convex set). In the integer setting, a general approach to deal with this
 958 formulation was introduced by [211]. In [234] a progressive hedging algorithm and Taboo search are used
 959 to address multi-stage problems with mixed 0-1 variables. The approaches can become somewhat com-
 960 putationally less demanding if recourse variables are instead continuous, which is often the case in UC.
 961 In fact, here commitment variable are typically first-stage decisions, to be taken well in advance, while
 962 the actual energy production (usually continuous) is indeed managed in real time when the uncertain
 963 data (load, prices, ...) is revealed. Such a choice is made in [52] where RO is applied to UC with a 2
 964 stage approach. Restricting commitment choices to a first stage is a convenient simplification but it does
 965 not fully represent reality, where (a few) changes to the commitment of units are in general possible.
 966 Accounting for recourse decisions, however, significantly increases the complexity of the problem, which
 967 justifies why restricting integer decisions to the first stage is the most common approach.

968 *4.1.2.2 Direct approaches vs. decomposition.* Regardless of the simplifying assumptions on UUC, the
 969 resulting mathematical program is frequently a very-large-scale one, which means that decomposition
 970 approaches are especially attractive. In some special situations, direct use of MI(N)LP solvers remains
 971 possible. This is for instance the case of the *self-scheduling* of a single unit subject to uncertain prices,
 972 for which the deterministic problem has a low number of variables. Often, however, the deterministic
 973 equivalent (if any) of the uncertain problem is usually so large that it cannot be directly solved by use of
 974 MILP solvers, and decomposition is required. This can be achieved by variable duplication, relaxing non-
 975 anticipativity constraints, system wide constraints or by using Benders’ decomposition. The resulting
 976 sub-problems are then CCO (e.g. [379]), RO, deterministic (e.g. [367]) or stochastic programs (e.g. [74]).

977 We will now present more details on algorithms for Uncertain UC models using these three approaches.

978 4.2 Stochastic Optimization (Scenario-Tree) approaches

979 In this section we will discuss four common solution approaches to solving scenario-tree based versions
 980 of UC: the direct MILP approach and three decomposition methods.

981 A SO program with scenario-tree structure can be decomposed in at least two ways. Perhaps the most
 982 natural one is to relax the so-called *non-anticipativity constraints* and solve as many deterministic UC
 983 problems as there are scenarios. This is called the *Scenario Decomposition* approach [367] and includes
 984 well-known variants such as progressive hedging [321]. The alternative is to dualize the offer demand
 985 equilibrium constraints in each node to form a LD [74] and solve as many stochastic programming
 986 problems as there are units. This can be referred to as *Space Decomposition*, *Unit Decomposition* or
 987 *Stochastic Decomposition*, because one is basically optimizing a stochastic function, which in this case
 988 just happens to have an underlying discrete distribution. We will use Unit Decomposition, UD, to have
 989 a different shorthand from the Scenario Decomposition, SD. The discretization can be carried out after
 990 having formed the LD in an appropriate Banach space setting (L^1 -type spaces); see for instance [278].
 991 We refer to [329] for a thorough discussion on various alternatives.

992 A different applicable approach is Benders’ decomposition, cf. §4.2.4. It exploits the L -shaped structure of
 993 the problem, whereby the second-stage (recourse) variables corresponding to each scenario are unrelated,
 994 and therefore the corresponding subproblems can be solved independently, once the first-stage variables

are fixed [385]. This corresponds to seeing the second (or later) stage(s) as an aggregated expected cost function depending on first (or earlier) stage variables. Under appropriate hypotheses (e.g., no integer decisions in later stages) this expected cost function can be shown to be convex, and cutting planes based approximations can then be used to compute the solution of the master problem (e.g. [108]).

4.2.1 Mixed Integer Linear Programming

In [377] the use of UC tools in a deregulated market is discussed. In particular, under the assumptions that prices are stochastic and there is no market power or transmission constraints, a GENCO can solve a self-scheduling UC for each of its units independently, which however should be a SO model due to uncertainty on prices. A MILP formulation for (a basic) UC is proposed, along with three DP approaches to solve it. These approaches are used to produce a cost-based method to generate a distribution of energy prices, based on the assumption that in a competitive market the price should be equal to the marginal cost of the most costly committed unit.

In [305] a two-stage model is considered where the first stage decisions consists of commitment decisions and an offer curve, while in the second stage the dispatch is computed. Single unit or identical unit systems are considered, although the model with several units can not cope with minimum up/down times. The focus is essentially on obtaining the offer-curve. A DP principle is presented, but no numerical experiments are provided. A very similar model is considered in [371], wherein commitment decisions and offer curves are first-stage decisions and dispatch later stage decisions. The key focus of these papers is on the market mechanisms.

Hydro scheduling is looked at in a market-based setting in [136]. The problem integrates commitment decisions on the turbined output, which have minimal release rates. Expected gain from selling energy on the market is maximized, whereas volume-dependent water values are used in order to represent the cost of water as measured by the difference between the initial and final volume in the reservoir.

The authors of [46] propose a two-stage formulation wherein the first stage variables consist of bilateral contracts. Once these contracts have been selected, the market price is observed and a bUC is solved in order to meet the resulting load. The objective function consists of Markovitz mean-variance model related to expected profits. A specialized B&B method is used in order to solve the corresponding MILP problem; the numerical experiences cover a GENCO with 3 thermal units and up to 15 scenarios.

In [79] a weekly UC model is studied wherein profit of a GENCO depends on bids made on the market. The GENCO is assumed to have a non-linear non-convex effect on market prices, modeled through the use of piecewise linear functions and binary variables. The corresponding model is solved using a MILP solver, Lagrangian decomposition and two variants of Benders' decomposition (taken from [78]). The computed production schedule is a first stage decision, whereas all other stages and nodes in the scenario tree refer to different realizations of market settling. The Benders-based decomposition approaches are found to be the most interesting, despite the substantial implementation effort.

In [96] a two-stage model is considered where commitment decisions and bid prices are first-stage decisions, while total generation and energy matched in the day-ahead market are second-stage decisions (continuous variables). Uncertainty is mainly relative to the spot price, that enters in the generators objective function. The formulated MIQP has a quadratic second-stage cost function, which is linearized by means of perspective cuts [141]. The resulting problem with 10 scenarios and 9 thermal units is solved with a MIQP solver. In this vein we also cite [393], where the second stage economic dispatch problem, involving wind generation, is used for adding feasibility cuts to the first stage master problem. The main focus here is on deriving "robust" commitment decisions.

4.2.2 Scenario Decomposition

In [367] progressive hedging is used to solve a large-scale bUC with 100 thermal units and 6 hydro ones. A SD scheme is presented in [72, 73] for solving a two-stage bUC problem (with only a few thermal

units), wherein integer variables are restricted to the first stage. The non-anticipativity constraints are dualized by using Lagrangian multipliers, and the overall scheme is inserted into a B&B procedure in order to ensure that an optimal solution is obtained. In [296] a scenario decomposition is used, with the focus being on reserve requirements in a system with high wind penetration. In [294] the uncertain renewable production is coupled with the demand response in a market environment. In [297] SD is again used to solve a UUC where the uncertainty is caused by wind power generation, taking into account the network constraints. A decomposition approach mixing scenario and Benders' decomposition is considered in [383]. The investigated approach relies heavily on classical tools in deterministic UC, such as Lagrangian decomposition, Lagrangian-based primal recovery heuristics and Bundle methods, but needs no specific assumptions on the set of technically feasible schedules. A real-life problem with 136 thermal units, 22 hydro valleys, 96 time steps and 50 scenarios is solved.

1052 4.2.3 Unit (Stochastic) Decomposition

1053 The standard UD approach is proposed in [74] for a bUC with 50 thermal units; the demand constraints
1054 are relaxed, resulting in stochastic sub-problems which are then solved by DP.

1055 In [324] a multi-stage hydro-thermal UC problem is considered with random customer load. The load
1056 is observed after having chosen the commitment decisions, but the actual generation levels (including
1057 continuous hydro generation) are determined once that the load is known. The demand constraint is
1058 dualized in a general probabilistic space setting, then the probability measure is discretized; no numerical
1059 results are presented.

1060 A multi-stage stochastic programming is proposed in [277] to deal with a hydro-thermal UC with 25
1061 thermal units and 7 hydro units. Load uncertainty is addressed through the use of UD and DP for solving
1062 the stochastic sub-problems; Lagrangian heuristics are then used to recover a primal solution. Similar
1063 UD approaches are considered in [111, 161, 276].

1064 In [368], three uncertainty factors are integrated in the UC problem: load, fuel and electricity prices.
1065 The fuel requirement problem basically becomes the second stage of the problem, the first one being
1066 a bUC formulation. A Benders' decomposition approach is used to plug the second-stage cost function
1067 into the first stage, and a LR approach is used for the first stage. This method is tested on a UUC with
1068 33 thermal units and about 729 demand scenarios.

1069 In [21] a weekly (10 days up to a month) stochastic UC problem is considered. A UD approach is
1070 employed, where the LD is solved by a disaggregate Bundle method. The approach associates a set
1071 of weights with each node that effectively preconditions the LD; this preconditioning is reported to be
1072 crucial for performances. Problems having up to 2000 nodes are solved with the generating units of EDF.

1073 A weekly two-stage UUC is also addressed in [342]. Both stages have all time steps, and essentially
1074 each is a bUC problem; load, price and cost uncertainty are revealed between the two. The problem is
1075 decomposed using a LR-based approach that yields a stochastic programming problem for each unit.
1076 Lagrangian heuristics based on [159, 427] are employed to recover a primal feasible solution. The authors
1077 also present a MILP for market price settling and bidding in a competitive environment. They suggest
1078 to incorporate both features into a single model by moving bid/offer decisions and first day commitment
1079 decisions in a first stage, while all other variables are moved to the second stage. In [273] the authors
1080 consider a model, with focus on market mechanisms, wherein commitment decisions and offer curves are
1081 first-stage decisions and dispatch are later stage decisions. The authors apply a global LR-based UD for
1082 solving the thus formulated problem.

1083 In [278] stochastic Lagrange multipliers are used in order to decompose uncertain demand constraints
1084 that have to hold almost surely. The resulting dual function is the expectation of this stochastic Lagrange
1085 function. Uncertainty is then discretized into a finite set of random drawings in order to approximate
1086 the expectation, and Bundle approaches are used to solve the dual. In this two-stage procedure, integer
1087 variables remain present in the second stage.

1088 In [354] the UD approach to the stochastic bUC with uncertain demand is revisited in terms of Dantzig-
 1089 Wolfe decomposition (the equivalence between this and a LR approach solved by CP being well-known).
 1090 This results in a column generation approach where the Lagrangian subproblem, solved by DP on the
 1091 scenario tree, generates schedules for each unit that are added to the restricted master problem.

1092 4.2.4 Benders(-Like) Decomposition

1093 The L -shaped method can be used to decompose UC problems with several stages. In its basic version
 1094 a single cut is added to the first stage problem, whereas in advanced versions multiple cuts (e.g., one for
 1095 each subproblem) can be added. This may increase convergence speed at the cost of an increased master
 1096 problem cost; we refer to the discussion in [58, 59] on this topic. The recent on-demand accuracy Bundle
 1097 methods [106] can be thought to provide a tradeoff between the multi-cut and mono-cut versions [125].

1098 In [412] another approach is proposed for finding such a trade-off. In this method, which is applied to
 1099 a stochastic UC with load and generation uncertainty, scenarios are divided into (homogeneous) groups
 1100 and cuts are derived for each group, as proposed in [372]. Consequently, the dimension of the master
 1101 problem is smaller in comparison with the classical multi-cut algorithm, while less information is lost
 1102 compared to the single cut version. The authors also claim that heterogeneously grouping the scenarios
 1103 may result in even better CPU time. Results are presented for a large-scale thermal UC with ramp rates
 1104 and spinning reserves.

1105 In [14] short-term cascaded reservoir management—as opposed to the more traditional approach where
 1106 reservoir management is considered to be a mid-term problem—is considered wherein the gain function
 1107 is explicitly given and depends on the water level and turbinated quantity. Uncertainty is modeled as a
 1108 Markov chain having 6 states per time step, which is expanded onto a scenario tree in order to allow for
 1109 an LP formulation of the problem. This approach is compared with DP, nested Benders’ decomposition
 1110 (closely related to SDDP) and a decomposed DP approach, which essentially efficiently samples the state
 1111 space. Nested Benders’ decomposition is found to be computationally the most efficient approach.

1112 Benders’ decomposition is compared with MILP approaches in [79] (cf. §4.2.1) and proves to be in general
 1113 preferable. In [394], Benders’ decomposition is used to address UC problems under wind uncertainty.
 1114 The authors use sub-hourly time steps (10, 15 or 30 minutes) to account for rapid variations in renewable
 1115 generation. They also modify the standard approach by adding some of the second stage constraints to
 1116 the master problem.

1117 In [425] a two-stage UC formulation is considered. Similarly to most approaches load is revealed in
 1118 between the first and second stage and power output is determined in the second stage, but the latter
 1119 also contains integer commitment decisions related to quick-start units. The quadratic costs functions
 1120 are linearized to obtain a MILP formulation. Then, because the second stage contains integer variables,
 1121 the approach of [352]—essentially a Reformulation-Linearization-Techniques [351] with Lift-and-Project
 1122 cuts [24]—is employed to construct an approximation of the convex hull of the second-stage problem, so
 1123 that a multi-cut Benders approach can be used to approximate the second stage recourse cost function.
 1124 A problem with 5 units, up to 2000 scenarios and 16 time steps is solved.

1125 In [295] both LR and Benders’ decomposition are used in a parallel high performance computing environ-
 1126 ment for solving a network constrained stochastic UC where uncertainty comes from different sources.

1127 4.3 Robust Optimization approaches

1128 An early work using RO techniques is [338], where a market clearing problem is considered under some
 1129 UC-like constraints. The main idea is to use an *adaptive RO* approach which partitions the uncertainty
 1130 set and allows decisions to be specific to each subset. The constraints are then weighed in the master
 1131 problem. The results are compared with traditional RO and a worst-case fully anticipative approach.

1132 In [400] a RO approach is considered where the uncertainty set on the load is a simple interval, so that
1133 methods from interval LP (e.g., [85]) can be employed together with Benders' decomposition to solve
1134 the model. The main focus of the work is on network security. In [410] a similar interval uncertainty
1135 approach is compared with a scenario-based approach. The results show that the former is very sensitive
1136 to the choice of the interval but is quickly solved, whereas the latter yields more accurate solutions but
1137 it is more costly to solve.

1138 In [424] a 36 unit bUC with ramp rate constraints is considered which includes wind energy supply
1139 and demand behavior of the customers based on electricity prices. In this two-stage model, wind power
1140 enters under the guise of an uncertain budget constraint and the first stage is a day-ahead UC problem,
1141 while the second stage is performed once the wind supply is known. The problem is solved by applying
1142 Benders' decomposing to the linearized problem along with a CP algorithm. It is claimed that this model
1143 significantly reduces the total cost and can fully exploit the available supply of wind energy. The same
1144 approach is employed in [199] to solve a 30 unit UC with ramp rates and transmission constraints where
1145 demand and supply are considered to be uncertain.

1146 In [52] the model proposed in [199, 424] is extended to incorporate spinning reserve constraints, trans-
1147 mission limits and ramping constraints. The focus is on gauging the impact of robustness of the solutions
1148 on the efficiency and operational stability of the system. A two-stage adaptive RO model is used where
1149 the uncertainty set concerns the nodal net injection at each time period. In the first stage an optimal
1150 commitment decision is reached by using Benders' decomposition algorithm, while in the second stage
1151 the associated worst case dispatch cost is calculated. Results from empirical studies with 312 generators
1152 have been compared to those of deterministic models with reserve adjustments under three aspects: the
1153 average dispatch and total cost, the cost volatility, and the sensitivity of the costs to different probability
1154 distributions. The sensitivity of the results to changes in the uncertainty set is not investigated. A very
1155 simplified two-stage RO model is investigated in [36], where sensitivity to the choice of the uncertainty
1156 set is instead explicitly addressed. The recourse cost function is the worst case cost over a specific un-
1157 certainty set involving uncertainty on load; a simple recourse assumption makes the second stage trivial.
1158 In [250, 251] the model of [36] is expanded to take into account a huge uncertainty set which admits a
1159 representation as a "Markov chain". A budget of uncertainty constraint restricts paths to be "not too
1160 extreme"; a comparison is made against stochastic programming approaches.

1161 The authors of [362] consider RO for uncertainty on contingency constraints. The resulting optimization
1162 problem is reformulated as an equivalent MILP and solved with standard solvers. This work is extended
1163 in [398] by including transmission capacity constraints and by considering a two-stage robust optimization
1164 setting. Commitment (and integer) variables are restricted to the first stage so that the second stage
1165 becomes a continuous optimization problem, further reduced to an LP by linearization techniques. A
1166 Bender's decomposition approach is used for solving the model. In [198] a similar model and solution
1167 approach can be found, integrating (interval) uncertainty on wind generation. A budget of uncertainty
1168 constraint limits conservativeness of the model. Demand response uncertainty is added in [423]; the
1169 three stages of the model are brought down to two stages by a reformulation. Commitment decisions are
1170 restricted to the first stage and Bender's decomposition is again used for solving the problem. In [422]
1171 the authors add a convex combination of expected second stage cost and worst-case robust cost to the
1172 objective function. Uncertainty is restricted to load uncertainty and Bender's decomposition is employed
1173 for solving the model.

1174 In [3] a RO approach to the management of electricity power generation is presented using concepts
1175 borrowed from classic risk management, i.e., Value-At-Risk. In [169] a RO with the Affinely Adjustable
1176 Robust Counterpart (AARC) approach [39] is proposed to the longer term electricity production man-
1177 agement. AARC is a restricted and more tractable version of the Adjustable Robust Counterpart (ARC),
1178 where recourse variables are allowed to depend on the values of uncertain parameters, but only in an
1179 affine way. The same methods are looked at for weekly hydro reservoir management under uncertainty
1180 on inflows in [13, 20]. The hypotheses are set up in such a way that the resulting problem has a MILP
1181 deterministic equivalent, which is then solved by a MILP solver. Several comparisons with sliding deter-
1182 ministic approaches are presented. Finally, in [195] an adjustable robust OPF is suggested.

1183 4.4 Chance-Constrained Optimization approaches

1184 In many optimization problems involving a final observation of uncertainty for which no recourse actions
1185 exist, one cannot guarantee feasibility for all constraints. Rather, one has to provide solutions which are
1186 “reasonably feasible” under all except the most unlikely scenarios. This is also the case in UC, where,
1187 for instance, one cannot actually guarantee that the demand constraints will never be violated. This is
1188 therefore an ideal setting for CCO, where the desired safety level can be specified under the form of a
1189 probability. Two approaches are possible: either the safety level is set for each constraint (e.g., time step)
1190 individually, giving an Individual CCO program, or for the system as a whole, resulting in a Joint CCO
1191 program. While the ICCO is obviously less robust than the JCCO (see the discussion in [382]), the latter
1192 is in general significantly more difficult to solve, especially if one wishes to do this exactly (i.e., without
1193 artificially discretizing the underlying random vectors or approximating the probabilistic constraint).
1194 This explains why CCO (either Individual or Joint) models are the least employed in the literature on
1195 UC. However, it should be noted that these approaches have indeed been used in related problems such
1196 as power expansion and transmission ones [6, 347, 353], which need be formulated on a much longer
1197 time horizon than commonly considered in UC, and therefore crucially require taking uncertainty into
1198 account [353].

1199 Individual CCO was applied for the first time in [289] to solve a 100-units bUC where the uncertainty
1200 of load has to be met with a high probability. The problem is then decomposed by using LR, and the
1201 subproblems are solved by DP. The results show that solving the CCO UC produces better (less costly)
1202 solutions than a deterministic UC with spinning reserves requirement.

1203 In [116] a ICCO UC model is formulated where different sources of randomness are considered. In
1204 particular, demand fluctuation, thermal units outage, uncertainty of wind generation and the schedule
1205 of flexible generating units. The individual chance constraints are converted into a deterministic model
1206 using the central limit theorem to recover a Gaussian model of uncertainty for outages. A standard
1207 MILP approach is then used to solve the problem. Again, the results are compared with these of a
1208 deterministic UC formulation, and the authors claim that the proposed model could be extended to
1209 basically any stochastic factor.

1210 A stylized UC model for hydro thermal systems under joint probabilistic constraints has been consid-
1211 ered first in [429]. The main focus there lies on dealing simultaneously with probabilistic constraints
1212 and binary variables, a significant technical feat. The suggested approach relies on the fact that some
1213 inequalities in the random system are more likely to be binding than others. This provides an ad-hoc
1214 way of reducing the difficulty for the JCCO (the experiments of [382] provide a rationale behind this
1215 approach). The reduced joint probabilistic constraint is then outer approximated by individual proba-
1216 bilistic constraints selecting appropriate weights. Finally, by using Hoeffding’s inequality an outer and
1217 inner approximation of these latter individual probabilistic constraint can be obtained. The resulting
1218 binary conic programming problem can be solved with a standard solver.

1219 In [397] a two-stage JCCO UC is considered with a joint probabilistic constraint for the use of wind
1220 power. The probabilistic constraint is not dealt with directly, but is discretized using a sample average
1221 approximation approach (e.g., [238, 239]).

1222 Joint probabilistic constraints in UC are dealt with exactly for the first time in [379]. Two sources of
1223 uncertainty are considered: randomness on load and on inflows for hydro reservoirs. In order to solve the
1224 JCCO UC problem, various decomposition approaches are investigated, among which LR and various
1225 forms of AL approaches.

1226 In [97] a DC Optimal Power Flow using an individual CCO approach is proposed considering the un-
1227 certainty of renewable generation. Under appropriate assumptions on the underlying distribution of
1228 uncertainty, and by reformulating the bilateral individual probabilistic constraints to two unilateral
1229 ones, the resulting problem can be shown to be equivalent to a second order cone problem. The conic
1230 constraints are then linearized by using a cutting planes approach. A real life instance over the 2746 bus
1231 Polish network is solved. It is interesting to note that such a network application with joint probabilistic
1232 constraints would give rise to differentiability issues, essential for the application of first-order methods;

1233 we refer to [183] for a thorough discussion of differentiability and an application to a stylized network
1234 problem.

1235 Finally, it is worthwhile to note that stability theory for CCO is developed in [323]; for recent references
1236 on such stability results we refer to [181, 182, 184, 322] and references therein. In particular, the authors
1237 explicitly consider stability results for probabilistically constrained power dispatch models, showing that
1238 the models are stable for several underlying distributions of the load, such as discrete or multi-variate
1239 Gaussian. However, no computational results are presented.

1240 5 Concluding Remarks

1241 The Unit Commitment problem could be considered an archetypal example of what makes optimization
1242 techniques both relevant and challenging.

1243 UC regards the optimal use of a highly valuable resource, energy, whose importance has possibly never
1244 been more strongly felt than in the present times. On the one hand, energy is a primary driver of, and a
1245 necessary requirement for, economic growth and improvement of peoples' living conditions. On the other
1246 hand, fair and sustainable energy production and distribution raises enormous technical, economical,
1247 organizational, and even moral challenges. While optimization techniques (and in particular their strict
1248 subset regarding the UC problem) alone cannot clearly solve all these issues, they can indeed give a
1249 significant contribution to the improvement of the efficiency of the energy system, with a substantial
1250 positive economical and environmental impact.

1251 From a technical perspective, UC arguably exhibits almost all possible characteristics that make an
1252 optimization problem extremely challenging. For a start it is not even a well-defined problem, but rather
1253 a large family of related problems that are as varied as the electrical systems worldwide. In almost all
1254 cases the problem is large- to very-large-scale, nonlinear, nonconvex and combinatorial. Thus, researchers
1255 continuously have to struggle between two contrasting needs: on the one hand providing more and more
1256 accurate models of the highly complex electrical systems, in order to allow better practical decisions,
1257 and on the other hand providing answers in the "unreasonably short" timeframe required by the actual
1258 operating environment. Furthermore, and perhaps more importantly for the present work, the operation
1259 of the electrical system requires a very articulate decision chain that spans from the decades (strategic
1260 decisions about the investments in new generation and transmission equipment, and even about funding
1261 of research capable of producing better ones) to the split-second range for on-line tracking of actual
1262 demand. This in turn means that uncertainty on the actual future status of the electrical system, and
1263 therefore on the consequences of the decisions that have to be taken here and now, is inherently present
1264 at all levels of the decision chain. This justifies the interest for techniques capable of dealing with
1265 uncertainty in energy optimization problems, and in particular in UC; whence the significance of this
1266 survey.

1267 While UC cannot be presently considered a well-solved problem, and much less so UUC (which has
1268 arguably been tackled only relatively recently), research on such an extremely challenging problem will
1269 likely have positive side-effects. Indeed, the tools and techniques that will be developed will almost surely
1270 find applications in many different fields, other than the optimal management of the energy system. This
1271 has already happened for the methodological and algorithmic developments of [99, 128, 141, 311], that
1272 were motivated by the study of UC, but have since been applied to a much broader set of problems. We
1273 are confident that the study of UUC will lead, together with practical improvements on the efficiency
1274 and safety of electrical systems, to an analogous development of new ideas and techniques that will
1275 be beneficial for many other fields. Therefore, as a small stepping stone for researchers interested in
1276 broadening their knowledge in UUC, we hope that this survey may prove useful.

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1280 **List of acronyms**

UC	Unit-Commitment problem
UUC	UC problem under Uncertainty
bUC	basic UC problem (common modeling assumptions)
ED	Economic Dispatch
GENCO	GENeration COmpany
TSO	Transmission System Operator
MP	Monopolistic Producer
PE	Power Exchange
PEM	PE Manager
OTS	Optimal Transmission Switching
UCOTS	UC with OTS
MSG	Minimal Stable Generation
OPF	Optimal Power Flow
ROR	Run-Of-River hydro unit
X_1	set of technically feasible production schedules
X_2	set of system wide constraints
1281 \mathcal{T}	set of time steps
MILP	Mixed-Integer Linear Programming
MIQP	Mixed-Integer Quadratic Programming
DP	Dynamic Programming
SDDP	Stochastic Dual DP
B&B, B&C, B&P	Branch and Bound (Cut, Price respectively)
AL	Augmented Lagrangian
LR	Lagrangian Relaxation
LD	Lagrangian Dual
CP	Cutting Plane
SO	Stochastic Optimization
SD	Scenario Decomposition
UD	Unit Decomposition (also called space decomposition or stochastic decomposition)
RO	Robust Optimization
CCO	Chance-Constrained Optimization
ICCO	Chance-Constrained Optimization with Individual probabilistic constraints
JCCO	Chance-Constrained Optimization with Joint probabilistic constraints

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