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Invited Review

Survey of optimization models for power system operation and expansion planning with demand response

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ABSTRACT

With the implementation of demand response programs and its increasing penetration in the power grid, various new challenges to the grid's operation have emerged. As a consequence, optimizing the operation of the power grid and the allocation of demand response resources, in the short-term, medium-term and long-term, has become a fundamental problem. This survey presents a review of the optimization approaches in the literature for the integration of DR in three central problems in power systems planning, namely optimal power flow, unit commitment, and generation and transmission expansion planning. We also highlight important future research directions.

1. Context and motivation

The growing adoption of renewable energy generation has made the planning of power systems significantly more challenging. At the same time, the advent of smart grids has enabled and incentivized the development of demand response (DR) programs that employ customer demand, including residential customers, to provide ancillary services to the electric power grid. For example, DR can contribute to mitigating the impacts of fluctuating renewable generation. These developments motivate the importance of approaches to power system planning for both system operation and system expansion that integrate the optimal use of DR resources. The focus of this survey is on the integration of DR into three central problems in power systems planning, namely optimal power flow (OPF), unit commitment (UC), and generation and transmission expansion planning.

OPF models were conceived to solve the problem of generating and distributing energy optimally considering the transmission system (Momoh et al., 1999). These models can consider different energy sources on the generation side. Furthermore, the transmission system model can be either more detailed by considering an Alternating Current Optimal Power Flow (ACOPF) model or simplified by considering a Direct Current Optimal Power Flow (DCOPF) model.

UC models are used to determine an optimal operating plan for the generating units in the system so that the demand is met while optimizing a given objective. This is typically the minimization of the total cost of generation but it can also be the minimization of active power losses (Bingane et al., 2018) or other objective of interest. The complexity of UC models comes from the fact that they consider the implications of committing specific generating units, accounting for the costs incurred when starting up these plants as well as physical constraints when ramping up or down production (Tejada-Arango et al., 2019).

Capacity expansion planning models consider the operation of the power system over a long-term time horizon. By contrast with short-term or medium-term models, long-term models need to take into account the fact that energy demand grows over time and that the current installed capacity eventually may no longer suffice to supplying this demand adequately. Thus, there is a need to build additional generation capacity and to expand the transmission system to guarantee sufficient energy supply over a long time horizon with minimum investment cost (Hemmati et al., 2013a; Meza et al., 2007; Unsihuay-Vila et al., 2011).

Demand response (DR) can be defined as the ability to change the energy demand so that one can alleviate energy demand peaks (Albadi & El-Saadany, 2008). In order to implement DR in the power grid there are several options, which will be briefly explained in the next section. As a result of the fact that DR resources are so sparsely distributed throughout the power grid, operating them and the power grid at the same time in a coordinated fashion is very challenging. To overcome this difficulty, the concept of aggregator was developed. An aggregator is an entity

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that is responsible for the management of DR resources (Carreiro et al., 2017) and facilitates the integration of DR resources into the operation of the grid. Aggregators may be grid operators or they may be independent entities that interact with the grid via market or control signals. Regardless of the specific arrangements, this problem is still very challenging.

Although there are some reviews that approach some of the problems that interest us, such as Abdi et al. (2017); Robert et al. (2018); Shariatzadeh et al. (2015); Verma et al. (2018), none of them discuss both operations and capacity expansion planning problems considering DR. In Robert et al. (2018), even though they discuss the DR-OPF integration, they neither present models nor examine the DR-UC integration. In Verma et al. (2018), they review the techniques to handle uncertainty in smart grids, but they do not discuss DR-UC or DR-OPF problems. In Abdi et al. (2017), although the authors consider OPF problems in general, they only briefly discuss the inclusion of DR in OPF models. Finally Shariatzadeh et al. (2015) discuss very briefly the impacts of DR in operational problems. As a consequence, there is a need for a survey that explores in detail the operational models (OPF and UC) and the capacity expansion planning models that consider DR.

Our objective in this survey is thus to review the different approaches used to model and solve the problem of planning the operation of the power grid and of DR resources in a coordinated fashion. This survey explores both the deterministic power grid operation models and the power grid operation under uncertainty models, covering both operation and capacity expansion planning models. We are interested in identifying both the optimization techniques used as well as the modelling approaches taken to tackle these problems. We are also interested in highlighting the existing research gaps, both in terms of modelling needs and of relevant optimization techniques.

This survey is organized in five sections. After this introductory section, Section 2 introduces the key concepts considered in this survey, namely OPF, UC, Expansion Planning, and DR. Section 3 is concerned with OPF models, Section 4 with UC models, and Section 5 with Expansion Planning models. Section 6 gives concluding remarks and directions for future research.

2. Key concepts, definitions, and notation

2.1. Optimal power flow

A power grid is composed of buses, indexed by $m \in N$, which have power plants, indexed by $j \in Th_m$, as well as transmission lines, denoted by $\{m,n\} \in \Omega$. Loads are also located at buses, and we consider them below. An OPF model is a mathematical representation of this grid, and is concerned with its optimal operation considering the transmission constraints and minimizing costs (typically generation costs).

When formulating an OPF model, there are several variables of interest. The first ones are the active and reactive power generation, that are represented by T_{jm}, QT_{jm}, respectively. There is also the voltage magnitude at a bus, Vm_m, the active and reactive power injections in the 'to' point of the branch m, I^p_{emn}, I^q_{emn}, as well as in the "from" point of the branch m, I^p_{fmn}, I^q_{fmn}. Several parameters also have to be taken into consideration. In each bus there are the active and reactive power demands, D_m, Q_m, the shunt susceptance and the shunt conductance, B'_m, G'_m. As regards the transmission lines, there is their susceptance, B_{mn}, their admittance, Y_{mn}, and their turns ratio, Tn_{mn}. There are also the coefficients of the generation cost function for the thermal plants, $a^{Th}_{jm}, b^{Th}_{jm}, c_{jm}$. Finally, there are also the upper and lower bounds for all variables and for the transmission.

A general formulation of OPF is as follows:

- Objective function:

$$\min \sum_{m=1}^{N} \sum_{j \in Th_m} \left(a^{Th}_{jm} T^2_{jm} + b^{Th}_{jm} T_{jm} + c_{jm} \right) \tag{1}$$

- Active power balance constraint:

$$\sum_{j \in Th_m} T_{jm} + \sum_{\{m,n\} \in \Omega} I^p_{fmn} + \sum_{\{n,m\} \in \Omega} I^p_{enm} - G'_m Vm^2_m = D_m \; \forall m \in N \tag{2}$$

- Reactive power balance constraint:

$$\sum_{j \in Th_m} QT_{jm} + \sum_{\{m,n\} \in \Omega} I^q_{fmn} + \sum_{\{n,m\} \in \Omega} I^q_{enm} + B'_m Vm^2_m = Q^t_m \quad \forall m \in N \tag{3}$$

- Transmission constraints:

$$I^p_{fmn} + iI^q_{fmn} = -\frac{Vm_m}{Tn_{mn}} \left[\left(i\frac{B_{mn}}{2} + Y_{mn} \right) \frac{Vm_m}{Tn_{mn}} - Y_{mn} Vm_n \right] \quad \forall \{m,n\} \in \Omega \tag{4}$$

$$I^p_{emn} + iI^q_{emn} = -\frac{Vm_n}{Tn_{mn}} \left[\left(i\frac{B_{mn}}{2} + Y_{mn} \right) Vm_n - Y_{mn} \frac{Vm_m}{Tn_{mn}} \right] \quad \forall \{m,n\} \in \Omega \tag{5}$$

$$\underline{Vm_m} \le Vm_m \le \overline{Vm_m} \quad \forall m \in N \tag{6}$$

$$(I^p_{mn})^2 + (I^q_{mn})^2 \le \overline{S_{mn}}^2 \qquad \forall \{m,n\} \in \Omega \tag{7}$$

- Generation constraints:

$$\underline{T_{jm}} \le T_{jm} \le \overline{T_{jm}} \quad \forall m \in N, \forall j \in Th_m \tag{8}$$

$$\underline{QT_{jm}} \le QT_{jm} \le \overline{QT_{jm}} \quad \forall m \in N, \forall j \in Th_m \tag{9}$$

The objective function minimizes the generation cost of meeting the energy demand. As for the constraints, there are the power balance constraints (2) and (3), the transmission constraints (4)–(7), and the generation bounds (8) and (9). Because of (4),(5) and (7), this model is a non-convex non-linear optimization problem, and even checking its feasibility is strongly NP-hard (Bienstock & Verma, 2019).

Because of the computational challenges faced when solving the ACOPF model, the use of the DCOPF model is often proposed. To obtain the DCOPF model, one removes (3)–(7) and (9), and updates the power balance constraint accordingly. A new variable is also added, θ^t_n, that represents the voltage angle at bus n at time t. The following constraints are also added to the problem:

$$I^p_{mn} = B_{mn}(\theta_n - \theta_m) \quad \forall \{m,n\} \in \Omega \tag{10}$$

$$-\overline{S_{mn}} \le (I^p_{mn}) \le \overline{S_{mn}} \quad \forall \{m,n\} \in \Omega \tag{11}$$

An excellent introduction to the OPF problem is given by Frank & Rebennack (2016).

2.2. Unit commitment

The UC problem has a similar objective function to OPF but the focus of UC is on the physical constraints of the generating units. This requires additional variables for each power plant, namely the start-up, shutdown and on/off state variables, respectively $y^t_{jm}, z^t_{jm}, x^t_{jm}$. We also add the following constraints to the original OPF model:

$$x_{jm}^{t-1} - x_{jm}^{t} + y_{jm}^{t} - z_{jm}^{t} = 0 \quad \forall m \in N, \forall j \in Th_m, \forall t \in T \tag{12}$$

$$T_{jm}^{t} - T_{jm}^{t-1} \leq R_{jm}^{U} x_{jm}^{t-1} + S_{jm}^{U} y_{jm}^{t} \quad \forall m \in N, \forall j \in Th_m, \forall t \in T \tag{13}$$

$$T_{jm}^{t-1} - T_{jm}^{t} \leq R_{jm}^{D} x_{jm}^{t} + S_{jm}^{D} z_{jm}^{t} \quad \forall m \in N, \forall j \in Th_m, \forall t \in T \tag{14}$$

$$\sum_{k=t-T_j^U+1, k\geq 1}^{t} y_{jm}^{k} \leq x_{jm}^{t} \quad \forall m \in N, \forall j \in Th_m, \forall t \in T \tag{15}$$

$$\sum_{k=t-T_j^D+1, k\geq 1}^{t} z_{jm}^{k} + x_{jm}^{t} \leq 1 \quad \forall m \in N, \forall j \in Th_m, \forall t \in T \tag{16}$$

Constraint (12) ensures that a generating unit is not turned on and turned off at the same time period. Constraints (13) and (14) are the ramping constraints, and (15) and (16) are the uptime and downtime constraints. The generation bounds constraints also need to be modified so that the bounds only apply when the unit is on:

$$\underline{T_{jm}}^{t} x_{jm}^{t} \leq T_{jm}^{t} \leq \overline{T_{jm}}^{t} x_{jm}^{t} \tag{17}$$

$$\underline{QT_{jm}}^{t} x_{jm}^{t} \leq QT_{jm}^{t} \leq \overline{QT_{jm}}^{t} x_{jm}^{t} \quad \forall m, \forall j \tag{18}$$

Improved versions of some of these inequalities that lead to a tighter description of the feasible operating schedules for generators were proposed in Ostrowski et al. (2011).

More detailed presentations on UC problems can be found in Anjos et al. (2017) and van Ackooij et al. (2018).

2.3. Expansion planning

Unlike the OPF and UC models, expansion planning models are used to plan for the optimal operation of the power grid over a long-term horizon. When planning operation of the power grid over such a time horizon, one has to consider the expansion of both the generation capacity and the power transmission system. There are models that only focus on the former, some that only focus on the latter, and some that consider both problems.

Because expansion planning is carried out for a long-term horizon, the grid operation constraints generally do not include the unit commitment constraints. Moreover, expansion planning models typically consider a DCOPF model of the transmission system. A general formulation of the expansion planning model is as follows:

- The objective function is defined as

$$\min c_{op}^{t} + c_{te}^{t} + c_{ge}^{t} \tag{19}$$

where

$$c_{op}^{t} = \sum_{m=1}^{N} \sum_{j \in Th_m} \left(a_{jm}^{Th} T_{jm}^{2} + b_{jm}^{Th} T_{jm} + c_{jm} \right) \tag{20}$$

$$c_{te}^{t} = \sum_{m=1}^{N} \sum_{n=1}^{N} \sum_{k \in Te_{mn}} \rho_{kmn}^{t} \tag{21}$$

$$c_{ge}^{t} = \sum_{m=1}^{N} \sum_{l \in Ge_m} \rho_{ln}^{t} \tag{22}$$

with c_{op}^{t} being the total power system operation cost, c_{te}^{t} the total transmission system expansion cost, and c_{ge}^{t} the total generation expansion cost, and where Te_{mn} is the set of potential new transmission lines that can be built connecting nodes m and n, and Ge_m is the set of potential new energy plants that can be built at node m. The variable ρ_{ln}^{t} indicates that the potential plant l at node n is operational at time t, and the variable ρ_{kmn}^{t} indicates that the potential line k between nodes m and n is operational at time t.

- Transmission constraints:

$$I_{kmn}^{p} = B_{mnk}(\theta_{nk} - \theta_{mk}) \quad \forall \{m, n\} \in \Omega, \forall k \in Te_m \tag{23}$$

$$-\overline{S_{mnk}} \rho_{kmn}^{t} \leq (I_{mnk}^{p}) \leq \overline{S_{mnk}} \rho_{kmn}^{t} \quad \forall \{m, n\} \in \Omega, \forall k \in Te_m \tag{24}$$

- Generation plants bounds:

$$\underline{T_{lm}} \rho_{ln}^{t} \leq T_{lm} \leq \overline{T_{lm}} \rho_{ln}^{t} \quad \forall m \in N, \forall l \in Ge_m \tag{25}$$

- Expansion decisions:

$$\rho_{kmn}^{t} \geq \rho_{kmn}^{t-1} \quad \forall m, n \in N \forall k \in Te_m \tag{26}$$

$$\rho_{ln}^{t} \geq \rho_{ln}^{t-1} \quad \forall m \in N, \forall l \in Ge_m \tag{27}$$

$$\rho_{kmn}^{t} \in \{0, 1\} \quad \forall m, n \in N \forall k \in Te_m \tag{28}$$

$$\rho_{ln}^{t} \in \{0, 1\} \quad \forall m \in N, \forall l \in Ge_m \tag{29}$$

First, for each potential new transmission line, we add its respective transmission constraints. Second, the generation plants bounds for the potential new generation plants have the upper and lower bounds multiplied by the decision variable relative to building the plant. Third, the constraints for expansion decisions guarantee that if a new generation plant or transmission line is built at time t then this will be reflected in the time periods that follow, and that the expansion decision variables are binary variables.

We note that there are additional constraints that may be considered in an expansion planning model, such as precedence constraints between expansion projects or the possibility of having links between expansion projects (Thomé et al., 2019).

A thorough presentation of generation expansion problems can be found in Koltsaklis & Dagoumas (2018), and a detailed presentation of transmission expansion problems can be found in Hemmati et al. (2013b).

2.4. Demand response

Demand response is the ability to change consumption patterns according to the system operator's needs. This can be done by either shifting or reducing demand, typically by providing a benefit to customers that change their consumption habits (Deng et al., 2015).

There are three main actions that can be classified as demand response (Deng et al., 2015):

- Peak clipping or load curtailment: This is a reduction of the load at peak energy consumption times in order to avoid surpassing the maximum total generation capacity of the power grid.

- Valley filling: This is achieved using energy storage devices to store energy during off-peak periods, thus increasing off-peak consumption, and the stored energy is used during peak consumption periods without contributing to the peak.
- Load shifting: This consists of shifting an amount of energy consumption from peak to off-peak periods without lowering the total energy demand over the day.

Demand response has several potential applications in the operation of the power grid. It can be used: i) to mitigate the intermittent energy output of renewable energy sources (Bitaraf & Rahman, 2017); ii) to help alleviate congestion in the transmission system (Yousefi et al., 2012); iii) to guarantee voltage stability (Wang et al., 2011) or provide other ancillary services to ensure operational security in general (Lee et al., 2016); iv) to mitigate the need for expanding generation capacity on the grid (Malik, 2007).

There are two categories of DR programs: incentive-based DR (IBDR) and price-based DR (PBDR). IBDR programs directly incentivize users to either reduce or shift their consumption. Examples of existing IBDR programs are Direct Load Control and Emergency Demand Reduction. PBDR programs also incentivize users to change their consumption but do this via the pricing of electricity. The idea is that they will avoid consuming energy when the price is higher, and consume more energy when the price is lower. Examples of PBDR programs are real-time pricing and time-of-use pricing. More recently, the concept of time-and-level-of-use pricing was proposed to price DR in terms of both power and energy (Besançon et al., 2020).

When considering either IBDR or PDBR programs in optimization models, such as OPF, UC and expansion planning models, DR can be modelled as a variable, such as in Kwag & Kim (2012) for IBDR, and in Wu et al. (2013b) for PBDR. Alternatively, its impact can be considered directly in the final demand, such as in Govardhan & Roy (2016) for IBDR, and in Tumuluru et al. (2014) for PDBR. It should be noted that for IBDR, one can model DR through incentive value variables, such as in Abdollahi et al. (2011).

Coordinating the operation of DR resources within the power grid is a complex process because DR is provided by a large number of small providers. To overcome this problem, an entity called *aggregator* was defined to act as a middleman between the system operator and the DR resources (Carreiro et al., 2017). Although they facilitate the communication between the system operators and the DR resources, designing aggregators is challenging and there are several options for doing so, such as designing virtual power plants.

We refer the reader to Deng et al. (2015) for more information about DR and DR programs, and to Carreiro et al. (2017) for a recent survey on aggregators.

3. Optimal power flow

When integrating DR in the operation of the power grid, several different objectives can be considered in the modelling. In this section, we discuss OPF models that take DR into consideration. Because many of the parameters considered in this type of problem depend on data that cannot be predicted accurately, one really should take uncertainty into account. However, uncertainty is often not considered for two main reasons, the first being that the problems become too complex and, consequently, too hard to solve, and the second being that there is a lack of data to adequately model the uncertainty. We discuss both deterministic and stochastic models, including algorithms and techniques used to tackle optimization problems under uncertainty.

When considering DR in power grid operations, most models will consider what kind of DR program is implemented, impacting the choices of how DR is integrated in the model. Besides that, because of the challenges in coordinating DR resources, some of the proposed models consider that DR is offered through aggregators, and this also impacts modelling choices. There are models in which DR is offered through an IBDR program (e.g., Wang et al., 2015a), others in which it is offered through a PBDR program (e.g., Goel et al., 2008), and in some cases, both types of programs are considered (e.g., Sugimura et al., 2020). There are also models that simply do not consider the DR program through which DR is offered.

Another modelling choice is whether the transmission system is considered or not. If it is considered, as discussed in Section 2.1, the model for the transmission system model must be determined, typically it is the DCOPF or the ACOPF model. In most of the literature, either the transmission system is not considered or a DCOPF model is used. Because DCOPF models cannot directly account for transmission losses, some authors add constraints to approximate these losses and hence more accurately model the system behaviour. Losses can be directly computed in the models that use an ACOPF model, such as in David & Li (1993); Duan et al. (2019); Ghorashi et al. (2020); Goel et al. (2008); Nojavan & Seyedi (2020); Safdarian et al. (2014); Singh et al. (2010).

3.1. Purpose of DR integration in the grid

Most authors are interested in the adequate integration of DR into the power grid operation, such as in Bai et al. (2016); Cheng et al. (2018); David & Li (1993); Goel et al. (2008); Kara et al. (2021); Sharma et al. (2014); Su & Kirschen (2009). In some cases, the problem of optimal location and sizing of DR resources is considered, see e.g. Cheng et al. (2018). In Kara et al. (2021), the impact of uncertainty in allocating demand response resources is taken into consideration and evaluated.

DR can also be a key asset in dealing with the fluctuations of renewable energy sources. In these models, DR will help mitigate this issue by shifting loads, such as in Bie et al. (2016); Duan et al. (2019); Kies et al. (2016); Sugimura et al. (2020); Wang et al. (2015a).

There are also models that focus on the power grid operation security. For example, voltage stability is a very important issue for a secure operation of the power grid, and, in some cases, DR can be used to help in guaranteeing voltage stability and avoiding voltage collapses, such as in Nojavan & Seyedi (2020); Wang et al. (2011). In Wang et al. (2011), specifically, DR is only activated when there are critical events, i.e., possible voltage collapse scenarios. In Zeng et al. (2018), the authors propose a methodology for evaluating the reliability value of DR in power grids, creating the concept of capacity credit with that goal.

In addition, there are some approaches that use DR to manage congestion in the transmission system. In Yousefi et al. (2012), the authors consider both DR and flexible alternating current transmission system (FACTS) devices to manage congestion in the transmission system. In Singh et al. (2010), not only it is proposed using DR for congestion management, but it is also used to avoid locational marginal prices spikes. In Wu et al. (2019), a transmission line congestion probability measure is used to guarantee that the transmission system congestion will be less than a certain probability level. In Tabandeh et al. (2015), the authors also take into consideration possible transmission lines and generating units outages when using DR for congestion management. Furthermore, DR can also be used to enhance the reliability of the power system, which can be seen in Goel et al. (2008). DR resources are used in moments of contingencies, such as when there are transmission system limits violations.

DR is also used to help mitigate electricity prices volatility. More specifically, in Goel et al. (2007), DR is used to mitigate nodal price volatility. In some cases, when considering PBDR programs, price responsiveness is represented in terms of demand side bids, such as in Su & Kirschen (2009).

Alternatively, in Safdarian et al. (2014), the authors are interested in analyzing the impacts of DR on the power grid operation, such as system losses, voltage profiles and service reliability.

There is also the possibility determining the operation of the DR resources and the power grid in a coordinated fashion without the need of a centralized calculation. Instead, the problem can be solved in a distributed fashion, as done in Matsuda et al. (2019) using an alternating direction method of multipliers (ADMM).

In some cases, the cost of implementing the infrastructure necessary for DR is also taken into consideration as well as the optimal location for DR resources, as can be seen in Yu et al. (2018, 2019).

There are some approaches where the DR is considered in a more detailed fashion, not only having upper and lower bounds, but also having ramping rate limits and constraints for the time of use of DR resources. For example, in Kies et al. (2016) DR resources are modeled similarly to an energy storage system, with state of charge and decisions of power charged and discharged.

Although most of the models consider DR as a variable, there are some approaches that favour directly calculating a new demand considering the DR usage, such as in Ghorashi et al. (2020); Matsuda et al. (2019); Singh et al. (2010); Su & Kirschen (2009). In particular, Ghorashi et al. (2020) use a system of rewards and penalties so that customers adjust their demands according to the rewards and penalties offered to them by the operator.

3.2. Aggregators

Because the DR resources are often spread thin throughout the power grid and most of the consumers can only offer a very small amount of energy through DR, many models consider aggregators instead of each individual customer's DR.

In much of the literature in which aggregators are considered, there is no detailed modelling of aggregators, as one can see in Duan et al. (2019); Singh et al. (2010); Yousefi et al. (2012). As such, the impact of aggregators is the smaller number of variables and the tractability of the problem. However, in some cases, models for aggregators are developed. In Devine et al. (2019), the authors propose a model where the objective is to maximize the aggregators' profit for using DR both for energy supply and reserve capacity.

3.3. Operation planning under uncertainty

As mentioned earlier, when planning the operation of the power grid, there are several parameters that cannot be known accurately, such as demand, solar and wind energy generation. Therefore, there is a need to consider their uncertainty by transforming the original, deterministic, problem into an optimization problem under uncertainty. Broadly speaking, there are three main different modelling approaches for this purpose, namely stochastic programming, robust optimization and chance-constrained optimization.

Stochastic programming (SP) generally encompasses mathematical programs that consider uncertainty in some or all of their parameters. In this survey, SP specifically refers to the representation of uncertainty through a set of possible scenarios. For a more detailed introduction to stochastic programming, see Birge & Louveaux (2011).

Robust optimization (RO) models uncertainty through *uncertainty sets*. When using *uncertainty sets*, the solution of the problem has to be feasible for any value within the set. As a consequence, the optimal solutions of robust optimization problems tend to be more conservative. We point out that while one needs to know the uncertain data distribution when solving a stochastic programming problem, this is not the case for RO. A more detailed exposition of robust optimization can be found in Ben-Tal et al. (2009).

Chance-constrained optimization (CCO) problems approach the uncertainty in the problem differently. Instead of considering the expected value (like SP) or the worst-case scenario (like RO), CCO considers the probability of the constraints impacted by uncertain parameters to be respected. The classic article of Charnes & Cooper (1959) remains an excellent reference about CCO.

3.3.1. Stochastic programming

When solving a stochastic programming problem, regardless of modelling the problem as a two-stage or a multistage problem, the simplest way to tackle it is formulating it as a deterministic equivalent, i.e., writing it as a single optimization problem, such as in Bukhsh et al. (2015); Goel et al. (2007); Hu et al. (2016); Singh & Kumar (2017). However, this approach creates intractable problems when considering a large number of scenarios. Thus, many practical approaches use a scenario reduction technique to select a few scenarios that are representative of the uncertainty, see e.g., Sun et al. (2021); Tabandeh et al. (2015); Talari et al. (2018). Scenarios are typically generated using Monte Carlo simulation but not always. For example, Huang et al. (2020) use the probabilistic collocation method with the aim of reducing the number of scenarios needed for a good representation of the uncertainty.

Another issue with SO is that risk is often not well represented, which has prompted some authors to take into account risk measures. One can observe this in Sun et al. (2021), where the proposed model uses the Conditional Value-at-Risk (CVaR) measure to model the risk that is associated with the decisions made.

3.3.2. Robust optimization

The most straightforward approach to tackle an optimization problem under uncertainty with robust optimization is considering a single-stage RO problem, such as in Hu et al. (2018), the so-called static robust counterpart (SRC).

Nonetheless, in many cases, there may be some decisions that need to be made before the uncertainty is realized leading to a multi-stage RO problem, which can be reformulated by finding its adjustable robust counterpart (ARC), such as in Sheng & Gu (2019); Yu et al. (2018, 2019); Zhang et al. (2017). In general, due to performance considerations, decomposition methods are used to tackle this kind of problem. In most cases the column and constraint generation (C&CG) algorithm is used, since it has a better convergence speed, such as in Zhang et al. (2017).

In some cases, it is possible to know the distribution of some of the uncertain parameters of the problem, and a hybrid stochastic-robust optimization approach can be used, see e.g. Li et al. (2021); Sheng & Gu (2019).

Finally, some authors approach the uncertainty with information gap decision theory (IGDT), such as Ghahary et al. (2018). IGDT is very similar to RO, however, it considers variable uncertainty sets, i.e., the upper and lower bounds of the uncertainty set are not fixed.

3.3.3. Chance-constrained optimization

When solving a chance-constrained problem, one builds a non-linear optimization problem that can be solved directly, as done in Wu et al. (2019). However, the resulting non-linear optimization problems can be hard to solve.

4. Unit commitment

When solving UC problems, we are considering, besides the OPF aspects, the technical constraints of energy plants, such as when they can be started up or shut down, and their ability to ramp output up or down. Similarly to the case of the OPF problem, there are various benefits in taking DR into consideration when solving UC problems.

4.1. DR purpose in the power grid

Most authors are interested in integrating DR and power grid operation adequately, such as in Aghaei et al. (2016); Khodaei et al. (2011); Kwag & Kim (2012); Magnago et al. (2015); Parvania et al. (2013, 2014); Tumuluru et al. (2014); Tumuluru & Tsang (2016); Wu et al. (2013b); Zhang et al. (2015c). In Zhang et al. (2015c), DR can be a source of energy for reserve capacity.

DR can also be a huge asset in dealing with the fluctuations in renewable generation. In these models, DR mitigates this issue by shifting loads, such as in Bakirtzis et al. (2018); Bitaraf & Rahman (2017); Ikeda et al. (2012). In Mousavi-Taghiabadi et al. (2020), DR and plug-in electric vehicles are used to ensure the security of frequency dynamics, which is primordial and increasingly difficult in view of the increasing penetration of wind power generation. In Bakirtzis et al. (2018), differently from other models, the authors propose that industrial, commercial and residential DR should be considered separately. Specifically, commercial and residential DR resources are modelled as being supplied by an aggregator, which is not the case for the industrial DR resources. In Ikeda et al. (2012), the authors take into account the forecast error, although they do not model the problem using stochastic optimization. Finally, some approaches aim to minimize environmental impacts such as greenhouse gas emissions, see e.g. Hajibandeh et al. (2018); Zhao & Zeng (2012).

There are also models that focus on power grid operation security. In Lee et al. (2016), a security-constrained unit commitment (SCUC) problem is modelled and DR is used to ensure supply security. In Alirezazadeh et al. (2021), DR is used to supply reserve capacity in case of thermal unit outages. In Ansari & Malekshah (2019), DR is used to manage transmission lines outages. DR has also been considered for supporting frequency control and hence supporting the secure operation of the grid, as seen in Bao et al. (2017); Mousavi-Taghiabadi et al. (2020). In Bao et al. (2017), DR is used for both demand shifting and frequency control.

Furthermore, DR is also used to help mitigate the volatility in electricity prices. Specifically, in Abdolahi et al. (2019), DR is used to smooth the local marginal price.

Considering how the customers will respond to DR and how to make it more attractive to them is an important aspect too. This is explored in Bie et al. (2016) where the authors propose to measure the customers' comfort, in addition to setting an attractive price, when deciding how to request DR resources from them.

On the other hand, in Jiang et al. (2017), the authors focus on evaluating whether taking DR into consideration is the most beneficial alternative or not, and they also analyze how the net load baseline inflation impacts the DR and, consequently, the operation of the grid.

In some cases, the cost of implementing the infrastructure necessary for DR is also taken into consideration as well as the optimal location for DR resources, as can be seen in Yu et al. (2018, 2019).

Finally, there are some approaches where DR is modelled in a more detailed manner, not only with upper and lower bounds, but also with ramping rate limits and constraints on the time of use of DR resources, such as in Bitaraf & Rahman (2017); Jiang et al. (2017); Khodaei et al. (2011); Kwag & Kim (2012); Wu et al. (2013b); Zarei et al. (2019). In Khodaei et al. (2011), the authors propose an UC model, and hence the DR also has an on/off state variable.

Although most of the models consider DR as a variable, there are some approaches that favour directly calculating a new demand considering the DR usage, such as in Abdollahi et al. (2011); Govardhan & Roy (2016); Tumuluru et al. (2014). Specifically in Abdollahi et al. (2011); Govardhan & Roy (2016), it is calculated based on the incentive valued offered by the operator to the customers.

4.2. Aggregators

In much of the literature in which aggregators are considered, a model for an aggregator is not included, as one can see in Bakirtzis et al. (2018); Konda et al. (2017); Parvania et al. (2014); Zhang et al. (2015c). As such, the impact of aggregators is the smaller number of variables and the tractability of the problem.

Models of the aggregator are sometimes taken into consideration. In Bao et al. (2017), the aggregator offers the DR resources through a virtual power plant (VPP), and, consequently, DR becomes akin to a generation plant. In Tumuluru & Tsang (2016), the aggregation is done through finding an equivalent price elasticity at a system level, and, as a consequence, the authors were able to implement price-based DR through aggregators. Parvania et al. (2013) presents a model where the objective is to maximize the aggregators profit, DR contracts are aggregated, and different types of DR are considered separately. In Saebi & Nguyen (2020), a DR market model is developed for the aggregator to operate in, which is applied only at the distribution system level. The decisions about the use of DR resources at the distribution level are then used at the transmission system level. In Talari et al. (2018), the aggregators offer DR resources through DR contracts; there are both day-ahead DR and real-time DR contracts.

4.3. Operation planning under uncertainty

4.3.1. Stochastic programming

When solving a stochastic problem, regardless of modelling the problem as a two-stage or a multistage stochastic programming problem, the simplest way to tackle it is formulating it as a deterministic equivalent, such as in Ansari & Malekshah (2019); Gong et al. (2017); Han et al. (2017); Karangelos & Bouffard (2011); Saebi & Nguyen (2020); Wang et al. (2015b, 2016); Wu et al. (2013a). However, this approach creates intractable problems when considering a large number of scenarios. For this reason, many approaches use a scenario reduction technique to have a few scenarios that are representative of the uncertainty, such as in Hamdy et al. (2019); Parvania & Fotuhi-Firuzabad (2010); Rahmani et al. (2020); Sahebi & Hosseini (2014); Talari et al. (2017); Valinejad et al. (2017).

The practical performance issues have also led to the use of decomposition methods such as Benders decomposition (BD) which can be seen in Soltani et al. (2018); Vahedipour-Dahraei, Najafi, Anvari-Moghaddam, & Guerrero (2018); Zhang et al. (2015b). In particular, Huang et al. (2014) implements the Benders-based Branch-and-Cut that works by verifying whether every examined integer solution is optimal or not. If it is not, a Benders cut is added and the resulting problem is solved again. This process is repeated until it returns an optimal integer solution, or a fractional solution, or the problem becomes infeasible. This algorithm removes the need to solve a MILP problem several times, significantly improving the performance of BD.

Another way to tackle the performance issues is to use heuristics. In De Jonghe et al. (2013), the authors use the PIES algorithm to solve the problem, and in Khazali & Kalantar (2016), the PSO algorithm is used. Heuristics are also applied to multi-objective problems, such as in Hajibandeh et al. (2018) where a multi-objective multi-criteria decision making heuristic is applied, and in Furukakoi et al. (2018), where a genetic algorithm is used to solve the model. In Kiran & Kumari (2016), instead of using an heuristic, the authors apply lagrangian relaxation to the original model and they solve the new model in an iterative fashion.

Besides that, there is the issue that risk is often not well represented, which has prompted some authors to take into account risk measures. One can observe this in Wang et al. (2016), where the proposed models use the Conditional Value-at-Risk (CVaR) measure to model the risk that is associated with the decisions made. In Yin & Zhao (2018), the authors propose the use of the fuzzy stochastic CVaR to measure the risk adequately, since they aim to measure the risk associated with the wind power and DR uncertainties. In Huang et al. (2014), the authors use the Average Value-at-Risk instead of CVaR as a risk measure.

Finally, because of the lack of information about the uncertainty data distribution, in some cases the uncertainty of some parameters is modeled using information gap decision theory (IGDT), such as in Ahrabi et al. (2021) where a hybrid IGDT-stochastic programming model is developed.

4.3.2. Robust optimization

The most straightforward approach to tackle an optimization problem under uncertainty using RO is to consider a single-stage RO problem, such as in Heydarian-Forushani et al. (2015); Liu & Tomsovic (2015); Mahboubi-Moghaddam et al. (2016), and to solve it via the so-called static robust counterpart.

Nonetheless, in many cases, there may be some decisions that need to be taken before the uncertainty is realized. This leads to a multi-stage RO problem that can be reformulated by finding its adjustable robust counterpart (ARC), such as in Zhao et al. (2013); Zhao & Zeng (2012). In general, due to performance considerations, decomposition methods are used to tackle this kind of problem. In some cases BD is applied, as seen in Zhao et al. (2013), but in most cases the column and constraint generation (C&CG) algorithm is used because it has a better convergence speed, see e.g., Zhao & Zeng (2012).

In Du et al. (2020), the authors take into account adjustable uncertainty sets and use the affinely adjustable approach, generating an affinely adjustable robust counterpart (AARC), which is less conservative than the ARC.

Finally, some authors approach the uncertainty using IGDT, such as Ahrabi et al. (2019); Nikoobakht & Aghaei (2017).

4.3.3. Chance-constrained optimization

A CCO problem can be transformed with a non-linear optimization problem but this latter problem is often hard to solve. This has led to the use of solution methods or problem reformulations that make the model more tractable. In Tan & Shaaban (2020), the authors use the so-called Big-M method to linearize the model, and, similarly, in Wang et al. (2012), a MILP reformulation of the chance constraints is used.

Heuristics are sometimes used in order to find a good quality solution in a reasonable amount of time. In Azizipanah-Abarghooee et al. (2016), the authors propose an improved version of the jaya algorithm, which is a population-based method. Particle swarm optimization (PSO) is also employed in some cases, such as in Liu et al. (2019). In Zhang et al. (2015a), the authors apply PSO together with some of the genetic algorithm operators, such as the mutation and crossover operators.

5. Expansion planning

In this section, we cover the various capacity expansion planning models in the literature for generation and/or transmission expansion planning taking DR into account. When operating the power grid over a long-term horizon, different issues must be considered. Because energy consumption grows over time, it is expected that the generating capacity may not suffice to supply all the demand, and that the transmission system may not be able to transport all the energy to meet the demand. There is thus a need to plan the expansion of both generation and transmission. When tackling this problem, one may consider only one or both aspects. Moreover, modellers also make assumptions about the kind of DR program considered, and how it is integrated in the model. Moreover, when the transmission system is included in the model, one may choose how it is represented. Most of the models either do not consider a transmission system or consider a DCOPF model, but some models do use an ACOPF representation.

5.1. Generation expansion planning

The impact of DR on generation expansion planning is taken into account in articles such as De Jonghe et al. (2012); Malik (2007); Oderinwale et al. (2020); Samadi et al. (2013). It may be done with different possible goals.

Most approaches in the literature consider DR resources in order to minimize or delay investments in new energy plants, such as in Malik (2007); Samadi et al. (2013). In some cases, in addition to delaying investments, DR is also used to mitigate the variability of renewable generation, such as in De Jonghe et al. (2012). In Domínguez & Carrión (2019), the authors also consider the need to minimize greenhouse gas emissions, and DR also supports that objective.

Some authors, such as in Oderinwale et al. (2020), only account for DR with regards to how it impacts the operation of the power grid. The operation of the power grid is used to verify if the proposed expansion plan is optimal.

Finally, although DR is often represented using a specific variables for it, such as in De Jonghe et al. (2012); Malik (2007); Oderinwale et al. (2020), this is not always the case. In Samadi et al. (2013), DR is represented by calculating the new demand directly considering the electricity price.

5.2. Transmission expansion planning

There are several approaches in which transmission expansion planning takes into account the impacts of DR, such as in Kazerooni & Mutale (2010); Löschenbrand (2021); Özdemir et al. (2015); Qiu et al. (2017a); Rathore & Roy (2016); Xie et al. (2020); Zakeri & Askarian Abyaneh (2017). DR may be considered in expansion planning for various purposes.

There are models that consider DR resources to mitigate the variablility of renewable energy sources, such as in Qiu et al. (2017a); Rathore & Roy (2016). In Qiu et al. (2017a), the authors also consider system reliability, using DR to support reliability in the presence of large quantities of renewable generation. In Li et al. (2015), the authors consider potential outages of generating units and transmission lines outages. Congestion management issues also need to be considered, as seen in Hajebrahimi et al. (2015). In some cases, DR is used to reduce the need to build new transmission lines or to reinforce existing ones, such as in Zakeri & Askarian Abyaneh (2017). Besides that, in certain cases, the impact of DR is evaluated on the daily power grid operation in order to verify if a given transmission expansion plan is optimal, such as in Kazerooni & Mutale (2010).

We again point out that including DR in a model does not necessarily imply having specific variables and constraints for it. In fact, in Kazerooni & Mutale (2010); Özdemir et al. (2015); Rathore & Roy (2016); Zakeri & Askarian Abyaneh (2017), DR is not calculated directly, but rather it is the new demand, after DR is requested, that is calculated directly. In Kazerooni & Mutale (2010); Özdemir et al. (2015), this new demand value is calculated based on the price elasticity and on the electricity price, and in

Zakeri & Askarian Abyaneh (2017), besides these two factors, incentives are also taken into account.

5.3. Joint generation and transmission expansion planning

The impact of DR on joint generation and transmission expansion planning is taken into account in articles such as Anjo et al. (2018); Gbadamosi & Nwulu (2020); Guerra et al. (2016); Hamidpour et al. (2019); Jenabi et al. (2013); Khodaei et al. (2012); Saxena & Bhakar (2019); Unsihuay-Vila et al. (2011); Zhang et al. (2016a,b). As mentioned in previous sections, the inclusion of DR has several possible goals.

Some approaches in the literature consider DR resources to minimize or delay investments on new power plants as well as investments on new transmission lines, such as in Hamidpour et al. (2019); Saxena & Bhakar (2019); Zhang et al. (2016b). Others are based on the fact that DR can not only be used to delay investments, but it can also be used to manage the system balance in the presence of renewable generation, such as in Anjo et al. (2018); Gbadamosi & Nwulu (2020); Khodaei et al. (2012); Zhang et al. (2016a).

The work in Khodaei et al. (2012) examines the reliability of the grid after applying the proposed expansion plan. In this specific model, the reliability is measured using the loss of load expectation (LOLE) that must remain within given limits.

In some cases, the impact of the DR resources in the proposed expansion plan is analyzed in the daily operation after applying that plan, such as in Zhang et al. (2016b). More precisely, the idea is to analyze the impact on the peak load and the adequacy of the proposed expansion plan for grid operation.

Besides that, the problem of the optimal location and siting of DR resources in the power grid is also taken into consideration by a few models, such as in Guerra et al. (2016); Jenabi et al. (2013).

In Guerra et al. (2016); Unsihuay-Vila et al. (2011) there is also a preoccupation with regards to the environmental impacts when proposing an expansion plan. To mitigate those impacts, CO_2 emissions constraints are used as well as carbon capture technologies.

Furthermore, DR is sometimes integrated through an aggregator, such as in Hamidpour et al. (2019), which facilitates the procurement of DR resources by the system operator.

Finally, we note that DR is generally directly represented using a specific variable when modelling this type of joint expansion planning, as we can see in Gbadamosi & Nwulu (2020); Guerra et al. (2016); Hamidpour et al. (2019); Jenabi et al. (2013); Khodaei et al. (2012); Unsihuay-Vila et al. (2011); Zhang et al. (2016a,b). However, this is not always the case, and Saxena & Bhakar (2019) is a good example of that.

5.4. Expansion planning under uncertainty

5.4.1. Stochastic programming

Similar to what happens for operation planning, most authors model uncertainty as a single (deterministic) stochastic programming problem containing all the scenarios, such as in Asensio et al. (2017, 2016); Domínguez & Carrión (2019); Marañón Ledesma & Tomasgard (2019); Zheng et al. (2018). However, because of the computational performance issues of that approach, some authors use a scenario reduction technique to keep only the most representative scenarios, such as in Jin et al. (2013); Qiu (2018).

In order to consider more scenarios and larger problems, some papers rely on decomposition algorithms. In Qaeini et al. (2019); Qiu (2018); Zeinaddini-Meymand et al. (2019), the authors use the BD algorithm to solve their proposed models. Because BD has performance issues, enhancements to this method are employed in articles such as in Li et al. (2015), where the authors use an improved BD algorithm, which they call hierarchical BD (HBD). It works by solving, in a first phase, a relaxed version of the original problem, and then in a second phase, solving the original problem with the Benders cuts generated in the first phase. In Lohmann & Rebennack (2017), the authors also propose the use of BD to solve a mixed-integer non-linear optimization designed for expansion planning. However, instead of using generalized BD (GBD), they propose to dynamically overestimate the linear relaxation of the subproblems, avoiding the need to use GBD. Because the relaxed subproblem can be hard to solve in some cases, the authors further propose the use of nested Benders decomposition (NBD) to solve the subproblem. In short, BD coupled with NBD is used to solve the proposed model.

Some authors propose multi-objective stochastic programming models, which are often solved with heuristics. Hajebrahimi et al. (2015); Hejeejo & Qiu (2017) employ the nondominated sorting genetic algorithm to solve their models, while Qiu et al. (2016) use the multi-objective evolutionary algorithm MOEA/D.

Finally, because risk is often misrepresented in stochastic programming problems from a practical perspective, some approaches take into consideration risk measures, as we can see in Qiu (2018); Qiu et al. (2017b). In Qaeini et al. (2019), the authors use CVaR as a risk measure in order to generate risk-averse solutions.

5.4.2. Robust optimization

In the first step to use a RO approach, one only needs to design an uncertainty set, find its robust counterpart and solve it. This is the SRC approach that can be seen in Löschenbrand (2021). However, under uncertainty, investment decisions will impact future decisions. In this case, we face a multi-stage problem and an ARC formulation can be used to solve it, as in Dai et al. (2019); Huang et al. (2019). Because these problems can be hard to solve, decomposition methods are often used, such as in Zheng et al. (2019). it is also often the case that one has information about the distribution of the uncertainty that could be used in a stochastic optimization approach, but the knowledge of this distribution is incomplete. In these case, one can use the Distributionally Robust Optimization (DRO) approach, as seen in Zheng et al. (2019).

6. Conclusion

This survey has presented a review of operation and expansion planning models integrating DR resources. For operation planning, DR can be used for different purposes, such as mitigating the fluctuations in renewable energy generation and mitigating transmission congestion. For expansion planning, the main objective of using DR is to mitigate the need for building new power plants or new transmission lines. However, DR is often also used to support ancillary operational objectives.

In most cases, the transmission system is modelled using DCOPF or it is not considered at all. An ACOPF model is seldom employed in either operation or expansion planning models. Although this is understandable due to the fact that ACOPF makes the models computationally challenging to solve, this choice may lead to optimistic solutions. Considering that there are now high-quality convex relaxations for ACOPF, such as in Bingane et al. (2018) and Coffrin et al. (2015), it would be worthwhile to use these to find more accurate solutions.

With respect to DR modelling, we note that aggregators are often not considered, which may cause issues when tackling large-scale grids with many DR resources. It would be interesting to explore the impacts of aggregators on large-scale grids and how they can facilitate the integration and optimal use of DR. Moreover, in most expansion planning models, the impact of DR coupled with the expansion schedule is not analyzed from a daily operational perspective. Considering that the impact of using DR is more perceptible in day-ahead operation, it would be important to analyze how DR might impact expansion decisions.

Uncertainty is growing in importance for operation and expansion planning, and while there are several models that account of it in some way, this survey highlights the fact that only a few of them employ decomposition techniques, and, even in these cases, most of them do not consider any enhancement methods to improve the performance of those decomposition methods. Given that such methods are practically the only means to solve large-scale models of realistic sizes, a promising path for future research is to optimize the performance of these techniques specifically for these classes of models, as was done recently for hydropower maintenance models in Rodríguez et al. (2021). This would allow to apply the models to real-world power grids.

Finally, with regards to RO, we can observe that it is sparsely used to address uncertainty. It would be expecially interesting to explore the potential of applying the recently developed method of DRO to operation and expansion planning modelling.

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