State-of-the-Art Techniques and Challenges Ahead for Distributed Generation Planning and Optimization

Task Force on Distributed Generation Planning and Optimization
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***Abstract*—It is difficult to estimate how much distributed generation (DG) capacity will be connected to distribution systems in the coming years, however, it is certain that increasing penetration levels require robust tools that help assess the capabilities and requirements of the networks in order to produce the best planning and control strategies. The work of this Task Force is focused on the numerous strategies and methods that have been developed in recent years to address DG integration and planning. This paper contains a critical review of the work in this field. Although there have been numerous publications in this area, widespread implementation of the methods has not taken place. The barriers to implementation of the advanced techniques are outlined, highlighting why network operators have been slow to pick up on the research to date. Furthermore, key challenges ahead which remain to be tackled are also described, many of which have come into clear focus with the current drive towards smarter distribution networks.**

***Index Terms*—Distributed generation, active network management, linear programming, multi-objective programming, ac optimal power flow, wind power generation, distribution networks.**

I. Introduction

FOR Distribution Network Operators (DNOs) the challenges posed by high penetrations of Distributed Generation (DG) are numerous. In fully liberalized electricity markets (e.g., European Union), planning the siting and sizing of DG plants is, in many respects, not possible. Due to unbundling rules, DNOs cannot invest in generation facilities and are meant to provide DG owners with cost-effective connection means, irrespective of the technology or geographical location. In this context, uncertainties due to, for instance, planning consents or financial support surrounding DG investments pose DNOs with major challenges as to what, where and when to reinforce the system in order to deliver timely connections without the risk of stranded assets. This lack of certainty and planning coordination translates into distribution network operators often connecting DG plants in a 'fit and forget', case-by-case manner where only traditional reinforcements (e.g., new lines or transformers) are carried out. Thus, any sophisticated solution –albeit potentially more cost-effective for society in the long term– is potentially left behind.

Although it is an imperative for many countries to aggressively promote the connection of low-carbon and efficient generation technologies, different government policies and regulatory frameworks have resulted in different technical and economic drivers for DNOs towards the connection of DG. Depending on the incentives in place, DNOs not tied to unbundling rules might be able to increase network reliability or postpone reinforcements by investing in and operating adequately sited and sized DG plants. On the other hand, unbundled DNOs capable of determining optimal locational connection charges might steer the deployment of DG in areas that could potentially reduce their energy losses (or at least not worsen them). From a purely operational perspective, DG plants could also be encouraged to provide reactive power support if that is of concern for the DNO or the regional transmission network. This variety of cases where DG technologies can play a major role in distribution networks has in the last decade encouraged researchers and industrialists around the world to investigate the corresponding planning and operational aspects.

Whatever the particular driver for a DNO, e.g., to allow the connection of more DG capacity, to reduce energy losses, or to increase network reliability, these DG planning tools must take into account essential network constraints such as voltage and thermal limits. The inherent variability of demand and renewable generation (e.g., wind power) is an aspect that should also be considered. In addition, characteristics of actively managed networks (as opposed to the current 'fit and forget' approach), where control schemes employing real-time control and communication systems allow more effective management of different network participants, including DG plants, voltage regulation devices, storage and demand, need also to be accounted for.

This paper is structured as follows: First, section II offers a comprehensive review of the literature in the field, detailing the various methods and state-of-the-art techniques employed to date. Section III gives a description of a number of the barriers to implementation. Finally, section IV describes the key future challenges in this area, with conclusions given in section V.

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II. State-of-the-Art Techniques

The optimal accommodation of conventional and renewable DG plants has been approached in the literature from different angles but primarily taking account of technical and economic issues. This section presents a critical review of the various methods and state-of-the-art techniques employed to date.

A. Analytical Analysis

If only a given demand-generation snapshot scenario is taken into account, a specific technical aspect (or objective function) can be formulated analytically in such a way that it is possible to find the most beneficial DG capacity (or power injection) through a simplified set of equations and procedures. For instance, consider the simplified voltage drop formula for a given line section *a*-*b*:

$$\Delta V_{a-b} = P_b \cdot R_{a-b} + Q_b \cdot X_{a-b} \quad (1)$$

where a is the distribution transformer or substation, R and X the resistance and reactance of the line, and P and Q the active and reactive components of the load connected to b. Connection of a DG plant at b with active P_{DG} and reactive Q_{DG} power output alters (2)

$$\Delta V_{a-b,DG} = (P_b - P_{DG}) \cdot R_{a-b} + (Q_b \pm Q_{DG}) \cdot X_{a-b} \quad (2)$$

Equation (2) can be used to determine an 'optimal' nominal capacity (MW) and power factor (or Mvar) that either minimizes the voltage drop or avoids voltage rise beyond the statutory limit. If a similar analytical analysis is extended to a network and all possible locations for the potential DG development are assessed, then a quick overview of 'best' locations and sizes can be produced, for the snapshoot scenario considered.

This type of analysis, focusing particularly on power losses, was used in [1, 2]. However, while power losses can be studied in passive networks considering peak load scenarios – as is traditionally done – distribution networks with DG plants require the assessment of energy losses. Not only is this the actual yardstick used by DNOs but the inherent variable nature of demand and (renewable) generation necessitates it. Additionally, by neglecting other demand-generation scenarios, technical issues that might appear otherwise, such as voltage rise or thermal overloads, will not be accounted for since the analytical formulation only caters for a single technical aspect (although they can be included to an extent in the corresponding solution procedure). Another limitation is that only a single DG plant can be evaluated at a time, requiring a sequential procedure if multiple connections are needed. This separate evaluation of multiple DG plants might result in the 'sterilization of capacity' wherein inappropriately located and/or sized plant prevents connection of larger plant elsewhere. The incorporation of operational solutions such as coordinated voltage control or generation curtailment cannot be done either. Consequently, although analytical approaches are straightforward alternatives to assess DG siting and sizing, care must be taken as the results are only indicative and scenario limited.

B. Exhaustive Analysis

A single technical issue, such as voltage rise or power losses, can also be approached by exhaustively exploring the entire (or most of the) search space corresponding to the locations and sizes of DG plants that could be connected to a distribution network. Such an approach might be useful if discrete values (i.e., specific DG capacities) are preferable. However, the actual benefit brought by exhaustive analyses is that it is possible to cater for a number of technical issues and constraints. Indeed, with this more direct approach the objective function can be the combination of parameters or indices that represent different technical and non-technical aspects, although it will be very time consuming. This methodology was adopted in [3, 4] where the siting and sizing of DG plants was investigated considering technical impacts such as power and energy losses, voltage rise, and short-circuit levels, which were combined into a weighted-sum objective function. In [5], economic and environmental impact indices were also incorporated. Although a relatively straightforward technique, tuning the corresponding weighting factors to obtain a composite index becomes a non-trivial task that if not appropriately performed can significantly bias the results. Moreover, while exhaustive analyses applied to a single connection is evaluated for a specific demand/generation scenario is not necessarily computationally intensive; this is not the case when multiple connections and the variability of demand and generation are accounted for, increasing considerably the computational burden of the exhaustive analysis. However, it is important to highlight that the use of state-of-the-art distribution analysis software packages such as OpenDSS [6] might prove a robust, fast alternative for exhaustively exploring extremely large search spaces. Moreover, some metaheuristic optimization techniques (section II-E) can efficiently explore the search space, reducing the computational time to locate solutions.

C. Linear Programming

Linear programming (LP) has also been employed to address the capacity allocation and energy optimization issues. Fundamentally, the use of linear programming entails a linearization of the power flow or the linearization of the results from an ac power flow. It has been demonstrated through simulation that the resulting approximation inevitably introduces an error, but not a significant one in the context of discrete turbine sizes [7, 8].

In [9], a linear programming formulation of OPF is employed to assess the control of multiple DG plants. The objective employed is to minimize the annual active generation curtailment cost. The results presented illustrate the relative merits of tap changer and active and reactive power control. In [10] ac power flow is employed to calculate linearized sensitivity factors. The sensitivities are employed to characterize a range of constraints, such as voltage, thermal and short-circuit limits. The method is formulated as a linear program and solved with the objective of maximizing the capacity of DG, subject to typical network constraints and taking account of N-1 configurations. In [11] LP is applied to

the question of non-firm DG access to the network. The objective employed is to maximize the energy harvested from a section of network by optimizing the allocation of DG with voltage constraints removed. The operation of DG has also been considered in the literature again employing ac load flow sensitivities to optimize the allocation of curtailment among adjacent wind farms [12]. An advantage of LP is that it offers significant potential for development of operational methods and is a robust optimization method. However, from a planning perspective, ac optimal power flow approaches would seem to be a more rigorous means of optimization at this stage.

D. AC Optimal Power Flow

The well-known ac Optimal Power Flow (OPF) [13] has traditionally been used for economic dispatch, and is widely acknowledged by the electricity industry as a powerful analysis tool. The ac OPF is a non-linear programming (NLP) problem, for which many solution methods exist including some which are highly specialized to OPF problems. The ac OPF formulation can be adapted to have different objectives and constraints according to the study being carried out. For example, consider the minimization of power losses:

$$\min \sum_{l \in L} (f_l^1 + f_l^2) \tag{3}$$

where $f_{l,m}^1$ and $f_{l,m}^2$ are the active power injections at each end node (denoted 1 and 2) of branch *l*. The difference between the net injections at each end defines the line power losses. This objective would be subject to the standard Kirchhoff voltage law expressions, as well as a range of constraints that might include, for instance, bus voltage and line thermal limits. The Kirchhoff current law (active and reactive nodal balance), however, will need to be adapted to cater for the injection of potential DG plants.

$$\sum_{l \in L | \beta_l^{1,2} = b} p_b^L + d_b^P = \sum_{g \in G | \beta_g = b} p_g \tag{4}$$

$$\sum_{l \in L | \beta_l^{1,2} = b} q_b^L + d_b^Q = \sum_{g \in G | \beta_g = b} q_g \tag{5}$$

where $(p, q)_b^L$ are the total power injections into lines at bus *b*; and $d_b^{(P,Q)}$ are the active and reactive demands at the same bus. From the set of generation units, *G*, the power injections, (p_g, q_g), of those connected to bus b are also included. Thus, this relatively simple formulation would lead to 'optimal' siting and sizing of DG plants in a way that power losses are minimized subject to the considered constraints.

Indeed the ac OPF has been used to tackle many of the same problems described in the LP section above. This alternative use of an OPF-like method for the (power) loss minimization problem was reported in [14]. A similar formulation but with the objective of maximizing DG capacity across multiple sites has also been adopted in [15, 16]. However, in these three OPF-based approaches, only extreme cases of peak or minimum demand and passive operation of the network were considered.

The flexibility provided by a tailored ac OPF makes it possible to extend the analysis to cater not only for voltage and thermal limits but also for a number of complex aspects. It can incorporate multiple periods to deal with the variability and coincidence of demand and renewable generation. Advanced control strategies such as coordinated voltage control, adaptive power factor and generation curtailment can also be incorporated to evaluate potential benefits. The approach proposed in [17] embeds these characteristics to determine the maximum DG capacity able to be connected to a given network. More complex problems resulting from other network constraints commonly overlooked by DG studies, such as N-1 security, voltage step change, and fault levels are also viable within this approach [8, 18, 19]. As in other optimization techniques, the same core framework can also be used to investigate different objective functions, such as, for instance, the minimization of energy losses [20].

A number of solution methods can be adopted to solve the ac OPF problem: from special linear programming formulations to branch and bound techniques. Commercial solvers specialized for NLP problems include CONOPT, that uses a generalized reduced gradient, and, KNITRO, that uses interior points. Although, no practical method exists which can guarantee to find the global optimum of a non-convex NLP local optima can be found in most cases. A NLP-formulated ac OPF will, of course, not cater for integer variables such as tap positions or discrete values for DG capacities. It is possible to consider a Mixed Integer NLP approach, however, but this could potentially restrict the size of the problem depending on the capabilities of the solution method used with little benefit in the context of planning decisions. A notable example of this approach is in [21].

The use of multi-periods to mimic the variability of generation and demand results in a much larger problem in terms of the number of variables and constraints. In general this translates into longer processing times, that depending on the size of the problem it could be intractable. In such a case, the problem has to be scaled down by (mainly) reducing the number of periods. Methods for doing this include coincidence matching [17], 'typical periods' [22] or clustering.

Finally, it is important to highlight that given the nature of this classical optimization technique, the problem has to be formulated in a 'closed' manner. While it is possible to do so with certain technical (and non-technical) aspects, for instance with fault level calculation [18], this places a significant limitation as to what can be taken account of.

E. Metaheuristics

A metaheuristic method is defined as an iterative generation process which guides a subordinate heuristic by combining intelligently different concepts for exploring and exploiting the search space. Learning strategies are used to structure information in order to efficiently find near-optimal solutions. Complex and 'decoupled' technical and non-technical issues involved in power systems optimization problems can be easily modeled and included in the optimization process. Metaheuristics do not require the 'closed' formulation of the different aspects being addressed

as is necessary in classical optimization. Metaheuristic algorithms can also cater for mixed integer problems that are common in power system optimization problems.

With metaheuristics, the objective function can be of any type and take into consideration different objectives. This characteristic leads to multi-objective applications that are better suited to describe the complexity of the new distribution businesses [23-27] (see section II.F). On the other hand, all metaheuristic algorithms require a careful tuning of optimization parameters that are essential for finding a good solution without excessive computation time. The attention is then moved from the mathematical formalization of both objective function and constraints to the algorithm parameters, which should allow a compromise between quality of solutions and computing time. The actual challenge when using these techniques is then the tuning of the parameters that guide the optimization. Indeed, care should be taken to avoid premature or slow convergence, particularly in large scale applications.

This leads to probably the most discussed disadvantage of metaheuristics: their inability to find the global optimum. Indeed, they are very likely to find a reasonable solution, though there is no guarantee of exactly how good this is. Multiple runs are often used to counter this. Metaheuristic algorithms allow the planning engineer to find not only a single optimum point, but a family of near-optimum planning alternatives. This feature of metaheuristics is particularly useful in DG allocation because the DNO generally has little or no control on the DG integration and different planning alternatives can be necessary to face uncertainties and minimize risks.

1) Metaheuristic algorithms

There are numerous metaheuristic algorithms; Ant Colony Optimization (ACO), Artificial Bee Colony optimization (ABC), Tabu Search (TS), Particle Swarm Optimization (PSO), Simulated Annealing (SA) including Genetic Algorithms (GA). All these algorithms have been used to solve the problem of optimal allocation of DG.

GA mimics the process of evolution. The most promising individuals have greater chances of transmitting their genes to offspring. By so doing, the population, generation by generation, improves and, if the premature convergence is avoided, for instance, with a random mutation, the algorithm converges. GA have been used by the first authors that pioneered the problem of the optimal integration of distributed energy resources in the distribution system and since then it has been preferred to other meta-heuristic algorithms [28-31]. The reason of the success is that GA is intrinsically suited to solve location problems. The coding of a solution can be very simple, a binary vector with as many positions as the number of bus candidate to DG connection. The classical GA operators (selection, crossover and mutation) can be used simply and effectively with few or no changes. As in many meta-heuristic algorithms, high values of penalty factors can be added to the fitness function of those individuals that do not comply with the constraints. It should be recognized that with simple rules of thumb the parameters of GA (i.e., population size, crossover type, etc.) can be set quite easily to achieve a good optimization tool. Fuzzy GA have been proposed using fuzzy genetic algorithm approaches in order to capture the multi objective nature of problems [32]. Genetic algorithms have also been applied to consider optimal investment planning for DG in a market structure[33].

TS is a metaheuristic that guides a heuristic method to expand its search beyond local optimality, with the systematic prohibition of some solutions to prevent cycling and to avoid the risk of being trapped in local minima. New solutions are searched in the set of the points reachable with a suitable sequence of local perturbations (neighborhood). One of the most important features of TS is that a new configuration may be accepted even if the value of the OF is greater than that of the current solution. To prevent cycling, some moves are marked “tabu” for a number of iterations; the length of tabu list, the *tabu-tenure*, fixed or variable, guides the optimization.

The SA is an algorithm that combines combinatorial search with a very simple metaheuristic that follows the cooling process of materials. Following an appropriate cooling schedule, the SA has the potential to avoid local minima and converges to the global minimum in a reasonable computing time. The parameters to tune are the annealing temperature, the number of iterations at constant temperature and the cooling strategy. SA annealing has been used for multiobjective optimization to minimize energy losses, polluting emissions and contingencies. In [34] the authors proved that SA performed better than GA and TS on the IEEE 30-bus test system, but the comparison is difficult to be accepted because neither the GA nor TS were optimized as the SA was.

PSO makes use of a velocity vector to update the current position of each particle in the swarm. The position of each particle is updated based on the social behavior that a population of individuals, the swarm in the case of PSO, adapts to its environment by returning to promising regions that were previously discovered. Recently PSO has been used for DG allocation [35]. Comparisons have been made between GA and other metaheuristic methods, and in some cases PSO converged faster than other algorithms finding out good quality solutions.

ACO and ABC are based on the dynamic of the social insect population. The interactions are executed via multitude of various chemical and/or physical signals (e.g., bee dancing during the food procurement, ants' pheromone secretion, and performance of specific acts, which signal the other insects to start the same actions). The final product of different actions and interactions represents the behavior of social insect colony. ABC algorithms has been used for determining the optimal DG-unit's size, power factor, and location in order to minimize the total system real power loss [36, 37].

2) Multi-objective Programming

Some DG planning objectives are naturally conflicting; consequently in some cases there is no single planning solution that will satisfy all stakeholders. A multi-objective problem with conflicting objectives has no single solution, but a set of solutions, known as the Pareto set. The multi-

dimensional concept of ‘‘dominance’’ is used to determine if one solution is better than other solutions [38]. All of the non-dominated solutions constitute the Pareto-set.

Multi-objective optimization problems are solved by two fundamentally different groups of techniques. The first set of techniques uses preference information and the iterative repetition of a single-objective optimization problem, usually solved by Genetic Algorithms (GA). The most common techniques of this first group are the weighted-sum method and the ε-constrained method. In the former, all objectives are aggregated to produce a single objective problem (similar to [3-5], see section II.B), this method is then iteratively used to change the set of weights to find the Pareto set. In the ε-constrained method, one of the objectives is optimized while the rest are kept as constraints to find each one of the solutions of the Pareto set [26, 30, 39]. These methods are useful when there is strong *a priori* knowledge of the problem, or when a particular region of the search space is explored. However, a large number of iterations must be performed to find many solutions of the Pareto set, increasing vastly the computational requirements, especially when many objectives are being analyzed.

Another group of techniques, known as multi-objective genetic algorithms (MOGA), have been proposed in recent years to overcome the above mentioned deficiencies, and to provide a “true” multi-objective approach [40]. Indeed, MOGA are able to find many solutions of the Pareto set at once. Two of the most powerful multi-objective evolutionary algorithms are the Non-Sorting Genetic Algorithm – II (NSGA-II) [41] and the Strength Pareto Evolutionary Algorithm 2 (SPEA2) [32]. A key advantage of the use of MOGA is the opportunity of using complex objective evaluations in the formulation of the problem, which can include stochastic simulations, OPF analyses, and probabilistic approaches, to provide more realistic models for dispatchable and non-dispatchable DG and storage [22, 33, 42-44]. MOGA also permit to analyze a variety of technical, economical and environmental objectives in a single optimization framework [22, 43, 45-47]. Multi-objective methods by their nature find compromise solutions rather than a single solution. This is an advantage in terms of providing insight but a drawback in that it leaves it open to interpretation by different parties and the ultimate decision will rest with system planners and operators.

F. Probabilistic Analysis

Uncertainties related to DG are due to two main aspects: the variable nature of the primary energy source and the possible unavailability of the unit when it is required to generate. The combination of these aspects may lead to generation deficit, which can heavily compromise the security, reliability and quality of power supply. The increase in the complexity of distribution systems with DG requires the assessment of the random nature of network failures and generation availability [48].

In order to adequately address the uncertainties introduced by DG integration to distribution systems, probabilistic methods can be applied for network planning and optimization. Besides, stochastic models of renewable resources must be developed in order to represent the influence of the primary energy source variability on generation availability. The impact of DG on the reliability of distribution systems depends mainly on the operational mode and purpose of connection to the system along with the energy source which drives it. For instance, DG could mainly be used to supply power to a local load (e.g., industrial site or a house), exporting to the distribution network only when there is excess capacity. Depending on commercial arrangements, such a consumer will only pay (or will be paid) the difference between the energy consumed and exported. In this case, there is no benefit to system reliability (only to the consumer’s reliability). However, if DG operates in parallel with the network, then new considerations must be introduced for reliability modeling. The simplest alternative is to model DG as a negative power injection, which can have a positive impact on reliability since it represents a reduction in demand.

DG plants based on dispatchable and storable energy sources, such as biomass, can be more easily modeled since energy can be considered available in reliability studies. The only issue usually considered for unavailability of generation is the failure of the generating unit. This kind of DG tends to be more reliable. On the other hand, the units based on variable and non-storable energy sources, such as wind, small hydro and solar, require a more complex model in reliability studies, where the energy availability also needs to be represented.

Stochastic models for renewable sources have been developed for wind generation [49], small hydro power plants [50], solar generation [51], and biomass thermal generation [52]. In general, generation availability of all these sources is obtained by the combination of the availability model of the primary energy source and that of the generation unit.

Models for reliability evaluation of distribution systems with distributed renewable generation are based on three different approaches: analytical methods [27], Monte Carlo simulations [48] and hybrid models [53]. Analytical methods are applicable to DG of dispatchable energy sources. The Monte Carlo simulation approach is adequate to represent DG of variable energy sources and also to aggregate the load variation curve. The hybrid model aims to combine the advantages of the first two approaches in terms of computational efficiency and the representation of energy availability uncertainty.

In a general sense, it can be said that DG enhances the reliability of distribution systems especially if islanded operation is allowed. However, when the generation is based on variable energy sources, the benefit is reduced and can even be negligible if not properly planned. The probabilistic analysis is able to properly capture this effect and to provide a more realistic response of the impact on the distribution system than the deterministic techniques.

However, probabilistic approaches have two most discussed disadvantages: the large amount of data required and the potential difficulty in interpreting the results and thus make decisions based on such results. The probabilistic

reliability evaluation or system planning requires the adequacy analysis of several system states or expansion alternatives that are performed by optimization methods [54]. Therefore, the use of efficient optimization methods in probabilistic analysis is crucial to have acceptable computation time. An approach that is being explored to reduce the computational burden is to use optimization techniques (classical or metaheuristics) for state space pruning in stochastic simulation [55].

G. Summary

The division of sections in the previous sections is along the lines of the computational methods employed. As is evident the problems and objectives of the methods cut across many of the computational methods. Table I summarizes the cross section of methods and objectives and their relationship based on the extant literature. It is evident that the siting and sizing of DG has been a focus with objectives ranging from minimization of losses to maximization of installed capacity to multi-objective approaches taking account of a number of objective simultaneously and examining the trade-off between them.

TABLE I
SUMMARY OF TECHNIQUES AND OBJECTIVES

Techniques	**Objectives & Papers**
Analytical	Power losses [1,2]
Exhaustive	Multiple objectives [3,4,5]
Linear programming	Minimisation of curtailment cost [9] Maximisation of DG capacity [8,10] Maximisation of wind energy [11] Optimal curtailment allocation [12]
Optimal power flow	Power Losses [20, 21] Maximisation of DG capacity [14-19] Minimisation of energy losses [20]
Metaheuristics	Maximisation of DG capacity [22-31] Investment Planning [29] Multi-Objective [34-45]
Probabilistic analysis	Improved reliability [48-54]

III. Barriers to Implementation

There are numerous implementation challenges in integrating DG into power systems and these have been explored well at a research level in recent years [56-58]. Many of these have been viable solutions and some of those have found their way into application in different regions around the globe. For example, one of the initial major moves to overcome DG connection and integration barriers was updating grid connection standards [59, 60]. Along with the DG technology and economics issues, the network challenges for DG integration are in the ‘planning’ and ‘operational control’ areas (or time frames). Two major barriers to implementation lie in the fact that DNOs are not used to using custom (if any) optimization codes and that some of the proposed techniques cannot consider a sufficient range of scenarios to tackle real world problems.

Techniques for planning have been the focus of the discussion in the sections above and the DG optimal siting and sizing problem (and proposed solutions) has been noted. In addition, there are challenges in adequately and economically planning the sizing of distribution network circuits for DG connection. This is problematic since the techniques for managing the operation of connected DG have a large role to play in assessing the required capability of the distribution network. Earlier work in this area simply attempted to sum up potential benefits and costs of DG to the network operator to establish the case for DG with a simplified approach to representing the through year operation [61].

The DG planning optimization approaches described above have some representations of the operational approach under consideration (e.g., in the OPF formulation of DG curtailment in [17, 43]) but fully representing each of the new approaches and their physical and operational characteristics and constraints is a non-trivial task. A further complicating factor is the uncertainty associated with these technologies (e.g., demand response, electric transportation, electric heating, energy storage) and where they will be connected and how they will be managed. There are already well established outcomes from studies on DG curtailment [17, 62, 63] to highlight DG access opportunities (or headroom calculations as they are sometimes known) and these prove useful in highlighting to power network operators and DG developers the opportunities for and level of network access. The treatment of uncertainty in DG planning is dealt with in section II-G but the uncertainty of the operational characteristics of DG is assessed alongside the viability of DG constraint management solution using a stochastic programming approach in [64].

On the demand side, the use of new data sources in distribution and DG planning and optimization is both a challenge and an opportunity. The wealth of data (and hopefully meaningful information) available from smart meter roll out programs provides a challenge to network planners (e.g., aggregation issues for domestic level data) but also a rich insight into the possibilities for DG deployment or network access at domestic scales upwards. It is anticipated that this will be an area of substantial development in the coming years based on early publication of results on this topic [65, 66]. The complete area of data capture, processing, modeling, estimation, forecasting as it relates to studies of DG and DG network integration seems to be of increasing importance.

A further issue for optimal network planning with DG using ‘active network management’ approaches is proper representation of the secondary communications and control infrastructure. On the one hand the cost of this needs to be incorporated into the network planning formulation and on the other hand the impacts of these secondary systems (e.g., on reliability of network connection) need to be evaluated.

This paper mainly deals with the planning issues of DG optimization and planning in the medium or long term, but there is a case now being made for operational optimization of DG. In part this is due to the maturing of active network management approaches and the requirement for DG network access to be maximized as far as possible. Some authors have proposed optimization approaches for DG control [67-70].

Some of the issues experienced with optimization approaches for DG operations are scalability of approaches for many DG units, robustness in finding a safe or feasible solution in control timescales, and the possibility of hunting for solutions in a dynamic environment.

The DG integration domain has transitioned from one of 'learning by research' to 'learning by doing' in the past few years. The advent of major stimulus or innovation funded smart grid project with DG as an integral ingredient has brought opportunities to develop, validate and demonstrate new approaches in DG integration. In the US the ARRA [71], in the UK the Low Carbon Networks Fund [72] and similar schemes elsewhere are at the stage of trialing very new approaches to DG integration. In most cases the emphasis on removing barriers to DG development is related to the low carbon emission characteristics of the DG technologies. The approaches being trialed include using energy storage, demand response, smart meter data, DG constraint management and other more active approaches to managing distribution networks [73].

One issue that has emerged is the issue of DNO capability to adopt the more innovative solutions available. The complexity of the planning and design process for networks with DG (and other new devices) and the integration of new operational approaches has initially resulted in relatively slow progress on deployment projects. This highlights a major problem for state-of-the-art DG planning and optimization approaches: 'DNO adoption'. DNOs have a substantial capability challenge to embrace whether receiving the results from more sophisticated planning tools or developing models themselves or accepting for internal use some of the tools and techniques emerging from research.

IV. Challenges Ahead

The move towards higher penetrations of DG is leading to DG constituting a high percentage of the overall generation plant mix. In systems with a few interconnections, this scenario poses many challenges. For instance, in Ireland it is now approximately 10% with instantaneous penetrations of 25% experienced at high wind power output. In the UK, DNOs are forecasting the connection of a further 10 GW of total DG capacity by 2015 [74], almost a quarter of the total new generation capacity expected by the system operator. This scenario requires DG to be considered in transmission planning and operation. The network planning methods developed to date have not addressed this issue and indeed it is non-trivial. It will require more integrated transmission and distribution models to properly assess the challenges and opportunities. In light of this, the focus on more traditional objectives such as losses is relevant but may have to be adapted to take account of wider system requirements beyond the distribution network level.

Ancillary services such as reserve, reactive power and inertial response are becoming the focus of much attention in recent times. These services which are not 'ancillary' but rather vital will in the future have to come from alternative sources other than the traditional bulk synchronous generation plant. The provision of such services from DG and the impact of DG at transmission is the focus of current attention by researchers [75-80]. From this work it appears that there is significant untapped capability from DG but also that additional sources of support may be required at transmission level [81].

Depending on the particular circumstances of a DG development, such as resource availability, planning consents or declared net capacity, it might be possible to have more than one network integration scheme (i.e., connection point and/or operation strategy) that is economically sound for the DG developer. The economics of different locations becomes even more relevant if not only are infrastructure costs involved but also distribution connection charges. Indeed, DNOs could tune the latter to steer DG projects towards specific areas where the technical and economic impacts on the system are less onerous or even beneficial. Alternatively, bilateral commercial arrangements between DNOs and DG developers could also provide win-win situations. However, for DNOs to determine appropriate locational signals or commercial arrangements they need to investigate how capable their networks are for integrating renewable or conventional DG. Such initiatives are particularly relevant where there is private ownership of DG. If the DNO does not own the DG and hence can only specify if given DG capacities are permissible, it is not in a position to specify a preferred overall allocation to maximize capacity, without entering into commercial arrangements such as those described above. If a global benefit is identified by an optimization method, this is often distinct from the regulatory and commercial framework in place and it may not be a trivial matter to translate a calculated potential benefit for the network into a delivered one.

Low-voltage networks are now also becoming the focus of attention of researchers and network operators. The potential uptake of micro-generation, electric vehicles and other demand side resources, coupled with developments in advanced metering have led to new modeling efforts of these networks. Challenges are present in the modeling of these networks alone, as historically they have not been modeled in detail by network operators. Beyond the modeling challenge, lies the development of optimization strategies and integration techniques for distributed energy resources, for which the techniques developed to date for DG will provide a solid foundation. For example, the distribution system planning and operation issues of electric vehicles are already the subject of several research studies [82-84], even though they are at a very early stage in their trial deployment in power networks and hence there remain many unanswered questions about their characteristics.

V. Conclusion

The rapid onset of DG in its various forms and scales is transforming the traditional planning and operation of distribution networks. The range of energy resources is matched by the range of computational methods and approaches employed in their integration. As outlined in this paper, each has their advantages and disadvantages and their

appropriate use is dependent on the particular case.

Many objectives have been pursued in the optimization of the planning of DG. Some of the most common include energy losses, maximization of DG capacity or energy via sizing and siting of DG, minimizing curtailment, or minimizing cost, oftentimes the reinforcement cost associated with DG. One of the drivers behind the appropriate objective is often the DG ownership model assumed. For example, a privately owned DG may care little about losses but would have a strong preference for the maximization of DG output. Multi-objective programming methods have tackled a number of these objectives simultaneously, in an attempt to show the range of 'compromise' solutions that may be possible.

The methods developed through research are in some cases now feeding more directly into the methods employed by network operators, or at least pointing the way towards the potential benefits of such approaches. Numerous demonstration and field trial projects led in many cases by network operators are underway across the world, in order to identify the realizable benefits highlights in the many works cited here. The status of DG is itself changing, with micro-generation, in particular photovoltaic cells and larger scale DG becoming more prevalent. As outlined here, this presents challenges in terms of network modeling, e.g., low voltage networks and wider system operation. Such developments point the way for fruitful areas of further research and highlight the dynamic situation and challenges all stakeholders in power systems are tackling.

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