

Optimal Deployment of Distributed Generation Using a Reliability Criterion

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Abstract—This paper presents an optimal planning approach toward the design of cost-efficient and reliable microgrids. The proposed approach uses simulated annealing (SA) to determine the optimal size and location of a mix of distributed generation (DG) candidate technologies to achieve stipulated reliability criteria. The deployment plan consists of adding suitable quantities of DG at appropriate locations, and is optimal in that the cost of expansion is minimized. The paper develops the models and the approach, and describes a SA-based implementation. The method is demonstrated on a standard test system, and the application of the method as a planning tool is illustrated by means of two case studies: (i) optimal expansion of an existing distribution system into a microgrid, and (ii) evaluation of the impact of projected prices on the deployment strategy. Relative penetration of different DG technologies is also analyzed.

Index Terms—distributed generation, microgrid, reliability, simulated annealing, siting and sizing.

I. INTRODUCTION

THE past decade has witnessed a global movement toward the deployment of distributed and renewable resources. Several considerations have contributed to this phenomenon, most notably the need to reduce dependence on fossil fuels, environmental concerns, avoidance of the time and cost of transmission and distribution (T&D) expansion, and government subsidies. These distributed generators (DG) are being deployed at or near load centers, i.e., in distribution systems, which are evolving into weakly meshed networks, or *microgrids*, in order to realize the reliability and economic benefits of DG. This evolution motivates the development of strategies for optimally augmenting distribution systems to form microgrids.

The problem of DG deployment, in terms of sizing, siting, or both, has been addressed in various forms in prior research [1]–[12]. Most researchers have approached the optimal deployment DG in the distribution network with different objectives such as minimizing capital and operating costs [1], [2], minimizing system losses [3], [4], maximizing DG integration [5], or improving the voltage profile across customer nodes [6]; some have combined multiple objectives [7], [8]. Others [9], [10] have focused on utilization of combined heat and power (CHP) mode of DG to benefit a compact cluster of loads. The work in [11], [12] deploy DG with objectives such as providing reactive support and other ancillary services, and

using DG as an alternative to T&D investments as demand increases.

Of all the benefits of microgrids, reliability is arguably one of the most compelling. It is a major consideration in cases where the cost per kW is an issue. Moreover, the ability to install DG at or near load points immediately opens up the opportunity to offer reliability-differentiated services. Although clear standards of reliability exist for transmission and bulk generation systems, such standards are still being defined for distribution systems in the presence of DG when connected mode operation is permitted. These considerations have motivated our attempts to develop methods for reliability-centered design and planning of microgrids and active distribution systems.

In our prior work [13], [14], we developed formulations for reliability-driven DG deployment that are amenable to optimization approaches based on dynamic programming (DP) and simulated annealing (SA). The success of these proof of concept demonstrations on small systems motivated the development of an expanded and more comprehensive method applicable to distribution systems (resulting in microgrids) of practical size. The method proposed in this paper is distinct from prior work on DG deployment [1]–[12] in that we *explicitly use reliability as a criterion (constraint) with the purpose of meeting reliability guarantees or targets* [15]. Reliability for distribution systems is quantified with several indices such as SAIFI, SAIDI, CAIDI etc. [16], [17]. However these indices reflect more of an operational practice rather than a planning perspective. In this work we use the energy index of reliability (EIR) [22], which is defined in section IV.D; due to its ability to capture the expected severity of outages, we consider it a more appropriate reliability index for system planning purposes.

In this paper, we develop a generalized deployment framework that allows optimization in both the size and location of DG, at minimum cost, subject to local and system-wide reliability targets (or guarantees). However, the framework recognizes that in certain conditions, for instance in case of co-gen (customer-owned generation) units, locations of specific DG units may be predetermined, and would no longer be subject to optimization. Similarly, the sizes of some units may also be predetermined. The deployment framework accepts these and proceeds to optimize those variables that are available for optimization.

A mix of candidate technologies has been considered for deployment. In general, DG can be classified into two major categories—dispatchable and intermittent—based on their characteristics. The power output of dispatchable DG, such as microturbines, fuel cells, etc. can be controlled within

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their capacity limits. Intermittent generation like photovoltaic, wind turbines, etc. are affected by the availability of their underlying resources such as sunlight and wind. The advantage of intermittent resources is that they do not incur any fuel cost. This paper proposes a method to determine the best mix of these candidate technologies so as to meet reliability requirements at minimum cost.

The various costs incurred by the addition of DG, both capital and operating, are considered in the formulation used in this work. Installation or capital costs are the costs of deploying the DG at different locations in the microgrid. These are considered to vary by location. For example if a DG (or a cluster of DGs) is installed in an urban area, it might cost more to place the DG near the downtown area than to place it in the suburbs. The cost of fuel used by dispatchable generators, and other operation and maintenance (O&M) costs are also considered.

The optimization tool used in this work is based on simulated annealing (SA) [18]–[21], and is used to determine the optimal size and location of a mix of DG candidate technologies in a microgrid to achieve stipulated reliability criteria. The expansion consists of adding suitable quantities of DG at appropriate locations, and is optimal in that the cost of expansion is minimized. The paper develops the models and the approach, and describes a SA-based implementation. The method is demonstrated on a standard test system, and the application of the method as a planning tool is illustrated by means of two case studies: (i) optimal expansion of an existing distribution system into a microgrid, and (ii) evaluation of the impact of projected prices on the deployment strategy. Relative penetration of different DG technologies is also analyzed.

The remainder of this paper is organized as follows. Section II defines the problem statement. Section III describes the component and system models. Section IV constructs the optimization framework, comprising the cost functions and the constraints. Section V describes the solution approach and implementation. Section VI presents the case study, results, and discussions thereof. Section VII provides concluding remarks.

II. PROBLEM STATEMENT

This paper defines a problem of cost optimal DG deployment in a microgrid with reliability stipulations. The optimization problem is defined with cost as objective function and reliability as a constraint. The problem is stated as follows: *determine the locations, sizes and mix of DG to be deployed from a set of candidate technologies in order to provide stipulated reliability guarantees at minimum total cost (both capital and operating costs)*. Mathematically, this is expressed as follows.

Minimize:

Annualized cost of DG deployment and operation

Subject to:

Reliability $> R_0$

System operating constraints

R_0 is the stipulated minimum reliability that the system is required to meet. In general, R_0 may be a scalar, representing a single (system-wide or locational) criterion, or a vector,

representing several criteria (system-wide and/or one or more locational reliability guarantees). A solution which satisfies the above conditions constitutes the optimal deployment strategy.

This formulation is in fact quite generalized. Although in our illustrations we use specific costs and indices, the framework described is generalized enough to permit inclusion of different costs and indices. Some of these variations are discussed in section VI.

III. COMPONENT AND SYSTEM MODELING

The component and system models and representation of operating conditions, as used in this work, are briefly described here.

A. Component Models

Generating units: Each generating unit is modeled as a two-state component (UP: available state; and DOWN: forced outage state) [23], [24], and is characterized by its peak generating capacity and forced outage rate. For intermittent units, typical historical data is used to determine the power output.

Distribution feeders: Each feeder is modeled as two-state and is characterized by its peak capacity, admittance and forced outage rate.

Loads: Bus loads are assumed to follow chronological profiles derived from load forecasts. For instance, in the case studies used in this work, hourly load forecasts over a one-year period were used.

B. Power Flow Model

The adequacy of supply at any load point in the system depends on both generation and transmission adequacy. It is therefore important to model the power flows appropriately. The method presented in this work can accommodate any suitable power flow representation that correctly models flows in distribution systems (radial or meshed). The power flow model used here can generally be stated as follows.

$$\text{Min } C_T = \left(\sum_{i=1}^{N_B} C_i \right)$$

Subject to:

Power balance conditions

Equipment availability and capacity constraints

C_T is the total system curtailment (i.e., power not served), C_i is the curtailed power at the i th bus, and N_B is the number of buses. The above model basically implies that for any encountered scenario (generation and feeder availability and load state) power will be routed through the network in such a manner as to minimize the system curtailment (load shed or demand not met).

In this work, for the purpose of demonstrating the concept, we use a linearized distribution power flow method, as described in [25], using only real power flows. This approach is considered appropriate in this framework because of the following reasons.

- 1) Reliability index calculation consumes more than 98% of the computational burden in the proposed planning process. This is due to the fact that state evaluation, which is necessary to calculate reliability indices, needs a large number of power flow calculations. It is essential to have a power flow method that is amenable to fast and robust heuristic optimization; the method used here [25] fits this need.
- 2) For planning studies involving DG, which typically has inadequate VAR capability, it makes sense to plan for real power generation first and then for VAR support. Traditionally, reactive power based planning [11] does not consider the outage probabilities of DG resources. It is prohibitive to consider reactive power capacities of DGs (which traditionally have limited reactive power capacity and are mostly operated at unity power factor) to plan for resource adequacy when load point reliability is a concern.
- 3) In this work, it is assumed that the DG will be installed at buses on three-phase primary feeders to improve the supply reliability in a distribution system, so unbalance is not a concern. If so desired, and if sufficient data is available, this model may be replaced with an AC optimal power flow model (with the system curtailment as the objective function) without affecting the validity of the proposed framework.

C. Fuel Consumption

For every hourly load scenario, dispatch solution producing the least curtailment provides the output from the DG units in the system. The output of each dispatchable unit is used to calculate the fuel consumed by that unit. At each node, the power available from intermittent sources, if any, is utilized before the dispatchable sources.

IV. MATHEMATICAL FORMULATION

In this framework, system planning consists of augmenting generation capacity to achieve stipulated reliability criteria. Two different types of DG, dispatchable and intermittent, are considered; these represent most of the DG candidate technologies commercially available today. Dispatchable generators are characterized by their peak generation capacity, and run on fuel. Intermittent generators have peak generating capacity, and their output varies based on solar insolation, wind etc. This section describes the formulation of the objective function in terms of the costs associated with deploying each of these types, and the constraints in terms of the reliability targets.

A. Annualized Capital Cost

This cost includes the depreciation on the capital cost of deployment. Let there be N_{dis} types of dispatchable and N_{int} types of intermittent technologies available to be deployed. The i th columns of solution matrices " F_{dis} " and " F_{int} " represent the selection of the capacities of the available candidate technologies at i th node in the system. Each matrix, " J_{dis} " of

dimension $N_B \times N_{\text{dis}}$ and " J_{int} " of dimension $N_B \times N_{\text{int}}$ is developed such that its i^{th} column contains the capital cost of deploying a MW of each type of DG at the i th node. A payback period is considered to recover the capital investment over which equal annual payments are made. These equal payment as a fraction of the total investment is computed as a payment rate " r ". The annualized capital cost can be computed as a product of total capital investment and payment rate r .

The annual depreciation on the capital cost for the system is given by Q_1 :

$$Q_1 = r \sum_{i=1}^{N_B} \left[\sum_{j=1}^{N_{\text{dis}}} J_{\text{dis}}(i, j) \cdot F_{\text{dis}}(i, j) + \sum_{j=1}^{N_{\text{int}}} J_{\text{int}}(i, j) \cdot F_{\text{int}}(i, j) \right] \quad (1)$$

where

r = Annual payment rate on initial capital

$J_{\text{dis}} = N_B \times N_{\text{dis}}$ deployment capital cost per unit of dispatchable type of DG

$J_{\text{int}} = N_B \times N_{\text{int}}$ deployment capital cost per unit of intermittent type of DG

$F_{\text{dis}} = N_B \times N_{\text{dis}}$ dimensional solution matrix where the i th column contains the capacities of each type of dispatchable DG to be deployed at node i

$F_{\text{int}} = N_B \times N_{\text{int}}$ dimensional solution matrix where the i th column contains the capacities of each type of intermittent DG to be deployed at node i

B. Fuel Cost

In general, the use (and cost) of fuel distinguishes dispatchable generators from intermittent. Most dispatchable DG require fuel for operation. To compute fuel cost the energy delivered by the dispatchable units should be computed for the whole year. Load as well as intermittent generation output changes every hour. Based on historical data, at every hour of the year, an optimal power flow is solved to determine the output from different generators. From the optimal power flow solution, the output from dispatchable generators is determined at every node for 8760 hours of the year.

The annual fuel cost Q_2 is computed as follows:

$$Q_2 = J_f \times \sum_{t=1}^{8760} \sum_{j=1}^{N_B} G_{j,t}^{\text{dis}} \quad (2)$$

where

J_f = Average fuel cost to produce a unit of energy

$G_{j,t}^{\text{dis}}$ = Dispatchable generator output at bus j for hour t

Within this general framework, solution of the dispatch problem for every hour of the year is computationally intensive. A reasonable approach has been taken to reduce the number of computations. Instead of 8760 hours in a year, average daily profiles have been used for four different seasons of the year. A day profile representing average of each for summer, autumn, winter and spring is generated. Energy output from dispatchable units is determined for every hour of these four days. The fuel cost for each season is a product of the energy consumed for the average day of the season and the number of days in that season.

The fuel cost now becomes:

$$Q_2 = J_f \times \left[\sum_{s=1}^4 N_s \sum_{t=1}^{24} \sum_{j=1}^{N_B} G_{j,t,s}^{\text{dis}} \right] \quad (3)$$

where

N_s = Number of days in season s

$G_{j,t,s}^{\text{dis}}$ = Dispatchable generator output at bus j for hour t of typical day in season s

C. Optimization Problem

The objective function is the sum of annual payments on capital cost and the fuel cost. Mathematically, the problem can be expressed as follows.

$$\text{Min } Q = Q_1 + Q_2 \quad (4)$$

Subject to:

$$\text{Reliability} > R_0$$

D. Reliability Measure and Evaluation

The proposed framework is general enough that a planner can select any suitable reliability index to specify reliability targets. In the implementation described here, we use the energy index of reliability (*EIR*) for this purpose. The *EIR* is defined as the expected energy served as a fraction of the total energy demand. We consider this measure to be appropriate for a distribution planning study because it is a severity index (as opposed to a probability index), and reflects the number of customers affected.

At every hour of the day, generation and load data is computed from the load profile and statistical generation output respectively. As mentioned before, an optimal power flow model is used to determine the minimum curtailment for any given contingency at every hour of every day. Then the *EIR* is obtained as follows: first the expected minimum energy curtailment is obtained by considering up to first order equipment (only generation) contingencies. This is performed for every hour of every day and the total expected energy curtailment is computed. The expected minimum energy curtailment divided by the total energy demand for the period gives the energy index of unreliability; this, subtracted from unity, yields the *EIR*. These steps are described in detail in [14].

The *EIR* of the system is given by:

$$EIR = 1 - \frac{EDNS}{E_{Total}} \quad (5)$$

where

EIR = Energy Index of Reliability

EDNS = Expected Demand Not Served

E_{Total} = Total energy demand.

The *EDNS* is the expected demand that the system is unable to serve as a result of outage events during a given period. It is calculated as the weighted sum of the curtailed demands, the weights being the probabilities of the corresponding outage events. It is expressed in MW/year.

As mentioned before, the proposed framework permits the use of any suitable reliability index. For instance, if sufficient data is available, the planner may choose to use an appropriate distribution system reliability index [16].

V. SOLUTION STRATEGY: OPTIMIZATION

The objective function, as well as the (reliability) constraints of the optimization, are non-linear. A heuristic method based on simulated annealing, as described below, is applied to solve the problem.

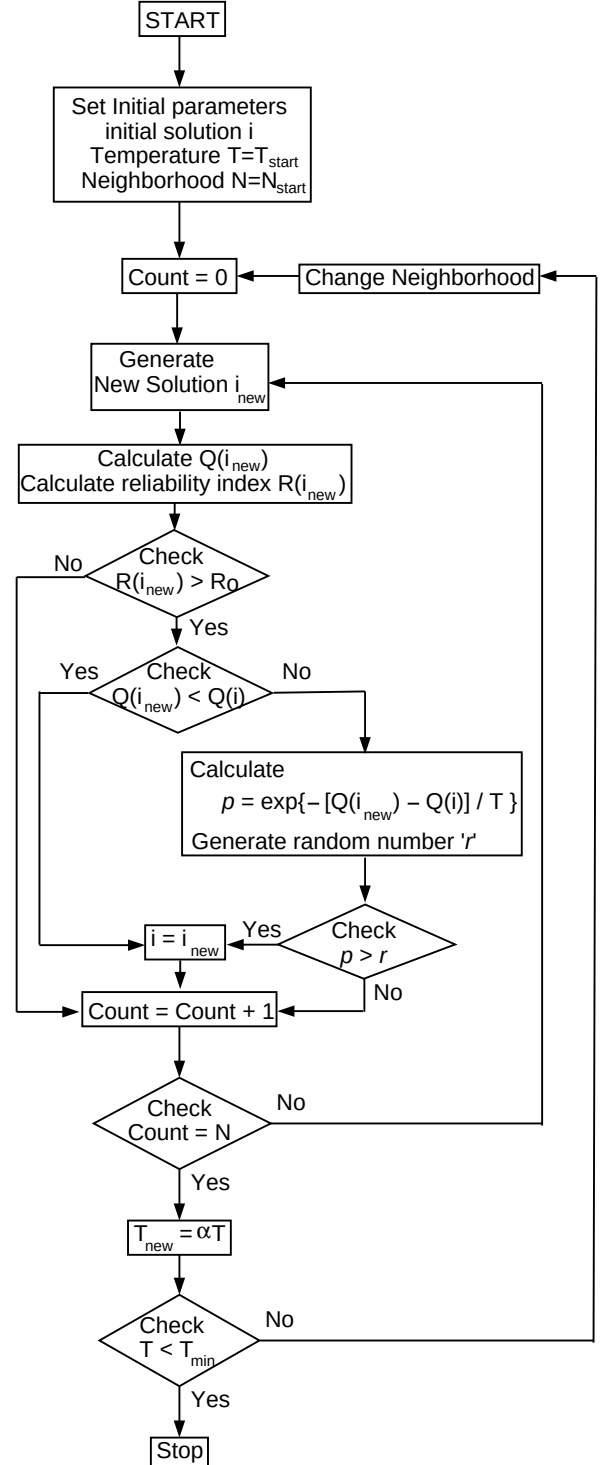


Fig. 1. Simulated Annealing Algorithm.

A. Optimization Using Simulated Annealing

Simulated Annealing is a stochastic global optimization technique which has an asymptotic convergence to the global

minima. It is derived from the idea of annealing in metallurgy [18]–[21]. At high temperature, the molecules move more freely and there is more randomness and at low temperatures there is less randomness and the organized lattice are formed. In annealing the metals are cooled slowly to reach a state of low energy to increase the size of crystals and reduce defects. Simulated annealing is analogous to this thermodynamic optimization. A parameter of temperature is introduced and the idea of slow cooling is introduced as to decrease in the probability of accepting worse solutions as the the solution space is explored. At high temperature the worse solutions are more likely to be accepted than at low temperatures. This method can ride over the local minima, as not only downhill moves are considered, but also uphill moves with a probability based on the Metropolis criterion [18]. The implementation of simulated annealing based algorithm is illustrated in the flow chart in fig. 1.

The solution space is the discrete space with limits between zero and the total deficit capacity in the system. The solution space might have a lot of local minima and few global minima. In the search, if only downhill moves are allowed, the search will get trapped into local minima. Thus, the initial acceptance probability of uphill moves is chosen to be reasonably high. At every iteration, a random solution is sampled in the current neighborhood. Initially, the neighborhood is chosen to be very large; it is subsequently reduced depending on the current best solution. The solution neighborhood finally gets concentrated around the global minimum.

B. Implementation

Two important factors that affect the optimization are temperature and neighborhood. Temperature is a factor that allows for the optimization to move rapidly from the existing solution that can be analogous to the state of molecules in a heated glass during the annealing process. Neighborhood corresponds to the boundary around the current solution within which a new solution can be chosen. The larger the neighborhood the more freedom to choose a farther solution.

At every temperature a fixed number of solutions are sampled in the current neighborhood. For each solution the new objective value is compared to the current one to determine if the solution is acceptable in the optimization. If the new solution has objective value lesser than the current one, it is directly accepted. But if the new objective value is greater than the current one, it is accepted with an acceptance probability given by

$$A_T(i, i_{new}) = \exp\left(\frac{Q(i) - Q(i_{new})}{T}\right) \quad (6)$$

This is how the optimization overcomes local minima. At higher temperatures several uphill (inferior) solutions are accepted, but as the temperature is reduced, the uphill moves get reduced. After a fixed number of iterations at a temperature, the temperature is reduced using a geometric cooling schedule.

$$T_{new} = \alpha T_{old} \quad (7)$$

A standard method is to assign a value of 0.9 to α [21]. After ten cooling schedules the neighborhood is reduced. In the

discrete solution space neighborhood size is reduced at every node by one unit. This process is followed till convergence is reached. The convergence is achieved if any of the following criteria is met.

Condition 1: Current global solution remains unchanged for 5 consecutive cooling routines.

Condition 2: The neighborhood is small enough to have a near-optimal solution.

Condition 3: The final temperature is reached.

The initial solution accelerates the optimization process. To start with, a capacity increase proportional to the load growth is assumed and is equally divided among all the nodes. It is expected that the optimization gets concentrated near global optima when convergence is reached. At lower temperatures, the search becomes a local search which will be sufficient when we approach the global solution.

C. Boundary Conditions

There are several techniques available to handle constraints. Boundary conditions arise from two reasons: (a) Practically there cannot be a negative solution for resource deployment in the microgrid. This is a linear boundary along each coordinate axis. If a solution is sampled in the infeasible space in any dimension it is limited by the coordinate axis in that dimension. (b) Reliability constraints: a fictitious wall is built along the boundary of these constraints. Only those solutions which fall on the feasible side of the solution space are considered. To prevent encountering a large number of infeasible solutions, the simulation is started with a large initial solution. A large initial solution provides sufficient flexibility for the optimization to move in different directions in the feasibility space. This has been observed to be an efficient way to handle the reliability constraints.

VI. CASE STUDY AND RESULTS

A. Test System Description

For the purpose of demonstration, we use a 13 bus test system that is obtained by simplifying the system connected to bus 2 of the RBTS [26], as shown in fig. 2. The system data is provided in tables I through III. A load growth of 100% is assumed for both the cases to justify the need for additional resources, and the feeder capacities are appropriately increased. Buses 1–7 are load points while buses 8–13 are interconnection buses with no load. The hourly load profile is obtained from FERC 714 filings [27] for the Arizona Public Service (APS) area for the year 2004.

Two candidate technologies—microturbines and photovoltaic (PV)—are considered for deployment to represent each of the dispatchable and intermittent generation. Insolation profile is extracted from statistical data for the area of Phoenix for a typical day in 2004. The load and PV output data are provided in the appendix. The total system peak load is 40 MW.

Based on estimates from EIA [28] and subsidies provided by APS, the average capital cost per MW of microturbine is taken to be US \$700,000 and for the PV module is US \$2M. The cost of deploying a unit of DG at the respective nodes is

C. Case II: Deployment Plans Based on Projected Prices

With increase in fuel prices it is inevitable that the projected prices will affect the deployment strategy. Also, as more subsidies are offered for renewable generation and technological advances result in better efficiency and lower prices of PV modules, there is likely to be a reduction in the deployment cost of PV. Other types of candidate technologies like wind have competitive prices compared to fuel based generators. Cases are studied to investigate the differences in the deployment plans when (a) 50% reduction in deployment cost of PV modules is projected and (b) 50% increase in fuel cost is projected.

TABLE VI
RESULTS FOR CASE STUDY II(A): 50% REDUCTION IN PV COST

Bus	Microturbines (MW)	PV (MW)	Bus	Microturbine (MW)	PV (MW)
1	0	0.8	8	2.7	3.5
2	0	0	9	2.2	2.9
3	0	0	10	1.7	1.9
4	0	0	11	2.6	3.4
5	0	1.9	12	0	0
6	0	0	13	0	0
7	1.1	1.9			

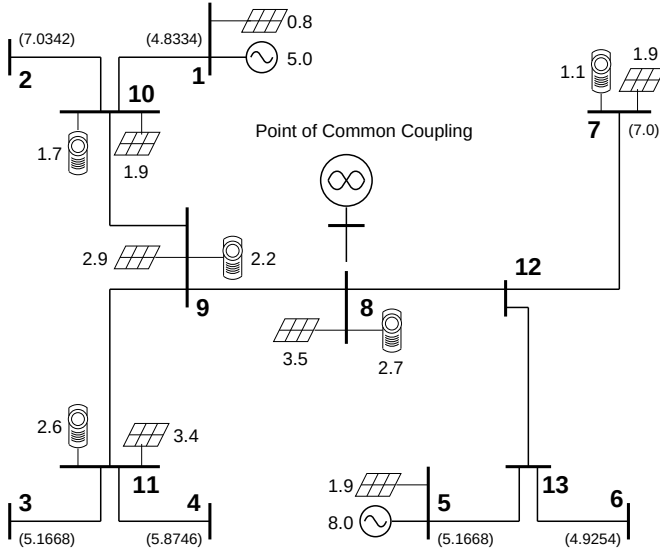


Fig. 4. Results for Case II(a): 50% Reduction in PV Cost.

Compared to Case I, PV deployment has increased by 33% in Case II(a). In Case II(b), PV deployment has increased by 18%. In Case II(a) the cost of a MW of PV is comparable to that of a MW of microturbines. Also the fuel cost makes PV very competitive. In Case II(b) The deployment cost per MW of PV modules is still higher than that of microturbines. But the fuel cost effectively makes total annual cost of microturbines significantly higher than that of PV modules. These competitive prices push the optimization toward higher penetration of PV as is clearly seen in the solution. The fuel cost incurred by microturbines is significant higher compared to the excess capital investment cost on the PV.

TABLE VII
RESULTS FOR CASE STUDY II(B): 50% INCREASE IN FUEL COST

Bus	Microturbines (MW)	PV (MW)	Bus	Microturbine (MW)	PV (MW)
1	0	0.8	8	3.9	3.9
2	0	0	9	1.3	1.7
3	0	0	10	1.8	1.3
4	0	0	11	0	0
5	0	2.9	12	0	0
6	0	0	13	0	0
7	3.6	3.8			

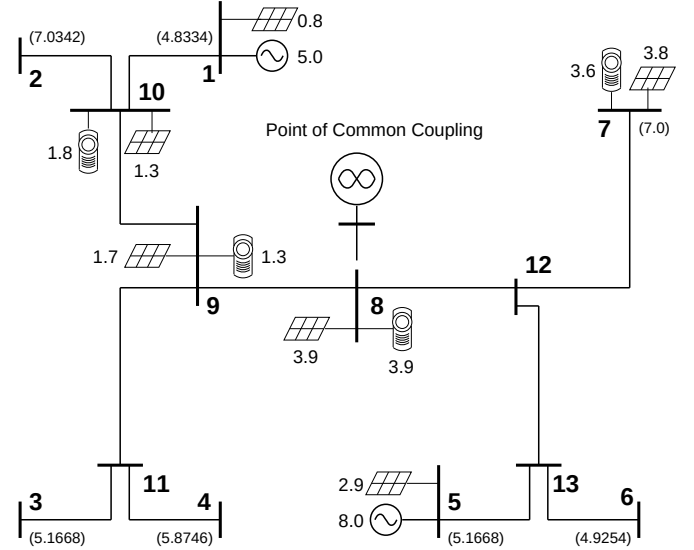


Fig. 5. Results for Case Study II(b): 50% Increase in Fuel Cost.

In both parts of Case II, the capacity of microturbines remains almost equal to that seen in Case I. This is because the capacity of dispatchable units was already low in case I, and further reduction would have resulted in reduced reliability. Also, microturbines have the ability to produce energy throughout the day, in contrast to PV. So a significant decrease in the microturbine capacity is not observed in either part of Case II.

This solution is structured towards a futuristic scenario and is also beneficial for the stability of the system. In this method PV is treated as purely intermittent, but with a decrease in cost of PV modules as well as storage technologies, hybrid systems can be developed which can be dispatchable in nature, with greater control on the generation output. This could boost a significant change from fossil fuel based generation to renewable energy.

D. Discussion

The distribution backbone in the test system is radial, as is typical of most systems in the US. All the load buses are located down the feeders which provide them with limited transmission capacity. It makes sense to put more DG upstream on the feeders compared to the load centers, because of (i) higher cost of deployment near the load centers compared to the substations further upstream, and (ii) higher available

transmission capacity giving more access to power transfer and higher reliability.

It has been observed that intermittent generation can have considerable penetration in the microgrid to exploit their cost benefits significantly. But dispatchable generation still becomes necessary to control and stabilize the system for load variations and changes in the output of the intermittent generation. Alternative fuels which are essential for dispatchable generators need attention to provide long term energy security. Also a hybrid system with storage can enable intermittent technologies to operate in dispatchable mode.

Appropriate choice of intermittent generation can be based on the correlation between statistical generation output and load profile. In summer peaking systems solar insolation follows close to the load curve and a similar pattern holds for wind profiles in winter peaking systems. Correlation provides sufficiency with lower installed capacity and thus lower deployment cost as well as operating cost. For instance, Phoenix, AZ has abundant solar insolation and, as expected, PV is a good choice for such a location.

The optimization problem is posed in a generalized form and can be used for many applications. For example, in the future customers may have enough generation capacity available and can quote prices to participate in grid support which is effectively a day ahead dispatch problem. This technique will help system operators to schedule a dispatch hierarchy ensuring reliability guarantee and system operation at minimum cost.

The optimization technique is very robust and can be implemented for almost any kind of cost function and constraints. The problem is formulated to accommodate generic models which give planner an option to choose parameters based on circumstances. SA being a heuristic approach can be used to solve highly non-linear cost functions and constraints. With proper choice of parameters and initial solution the optimization technique can reach very close to an optimal solution.

The problem of siting and sizing is computationally intensive. The majority of the simulation time is spent in computing reliability for every solution sampled by the algorithm. This formulation makes it amenable to solve the problem in a reasonable time.

VII. CONCLUSION

This paper presented a method based on simulated annealing to determine the optimal size and location and mix of DG candidate technologies in a microgrid to achieve stipulated reliability criteria. The paper described the development and implementation of the method, and demonstrated it with two case studies on a 13-bus distribution test system. The case studies demonstrated how the method can be used to expand an existing distribution system into a microgrid, and to investigate the impact of future prices on system expansion plans.

The proposed method is distinct from prior art in that it recognizes that reliability is a significant consideration in DG deployment, and constructs a framework that is completely driven by reliability specifications and operating constraints.

The framework presented here is generalized and flexible; it permits optimization of both the size and location of DG, but also accommodates cases where both are predetermined, such as in co-gens. The framework considers both dispatchable and intermittent DG types, and capital and operating costs. It can be easily extended to include other DG categories, and other costs. It can also be extended to permit siting single phase DG on secondary feeders, by extending the power flow constraints to include three phase flows. This is not difficult when using the power flow models described in [13] or [25].

The optimal locations of DG would normally be near the load centers. However, if a microgrid offers multiple deployment options with different costs, it may be prudent to determine locations and sizes of DG based on deployment cost rather than the sizes of proximal loads. This is borne out by the case studies reported in this paper.

VIII. APPENDIX: INSOLATION AND LOAD DATA

TABLE VIII
AVERAGE DAILY PV OUTPUT AS A FRACTION OF YEARLY PEAK

Hour	Winter PV output	Spring PV output	Summer PV output	Autumn PV output
1-5	0	0	0	0
6	0	0.0199	0.0418	0
7	0	0.1179	0.1819	0.0469
8	0.0623	0.3050	0.3876	0.1949
9	0.2184	0.5093	0.5806	0.3931
10	0.3959	0.6851	0.7469	0.5630
11	0.5337	0.8202	0.8748	0.6892
12	0.6220	0.9053	0.9559	0.7630
13	0.6547	0.9344	0.9844	0.7796
14	0.6296	0.9058	0.9586	0.7375
15	0.5485	0.8212	0.8800	0.6399
16	0.4168	0.6865	0.7542	0.4932
17	0.2440	0.5110	0.5896	0.3080
18	0.0821	0.3067	0.3977	0.1266
19	0.0064	0.1116	0.1924	0.0228
20	0	0.0126	0.0483	0
21-24	0	0	0	0

TABLE IX
AVERAGE DAILY LOAD PROFILE AS A FRACTION OF YEARLY PEAK

Hour	Winter load	Spring load	Summer load	Autumn load
1	0.4008	0.3980	0.547	0.4108
2	0.3943	0.3821	0.5173	0.3945
3	0.3928	0.3720	0.4952	0.3843
4	0.3966	0.3669	0.4806	0.3795
5	0.4112	0.3715	0.4783	0.3857
6	0.4466	0.3900	0.484	0.41
7	0.4964	0.4179	0.5037	0.4408
8	0.5195	0.4408	0.5426	0.4595
9	0.5083	0.4568	0.5881	0.4765
10	0.4886	0.4701	0.6292	0.4916
11	0.4740	0.4865	0.6751	0.5106
12	0.4590	0.5	0.7151	0.5267
13	0.4466	0.5134	0.7519	0.5418
14	0.4366	0.5271	0.7854	0.5561
15	0.4285	0.5386	0.811	0.5656
16	0.4249	0.5468	0.8275	0.5732
17	0.4297	0.5526	0.8331	0.5765
18	0.4604	0.5508	0.8229	0.5799
19	0.5001	0.5432	0.7926	0.5851
20	0.5019	0.5459	0.7628	0.5729
21	0.4949	0.5374	0.7426	0.5491
22	0.4830	0.5126	0.7027	0.5213
23	0.4521	0.47	0.6455	0.478
24	0.4168	0.4255	0.59	0.4354

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