

Optimization of Generation and Distribution Expansion in Microgrid Architectures

JOYDEEP MITRA, SHASHI B. PATRA, MALLIKARJUNA R. VALLEM, SATISH J. RANADE
Klipsch School of Electrical and Computer Engineering
New Mexico State University
Las Cruces, New Mexico 88003
USA

Abstract: With increasing penetration of distributed energy resources (DER), the nature of distribution systems worldwide will evolve. It is expected that such evolution will result in the formation of ‘microgrids,’ i.e., distribution networks that are connected in a grid-like fashion. This paper anticipates this, and proposes a rational approach to the architecture of such microgrids. The proposed approach consists of planning for the load growth in a given distribution system, and systematically developing it into an optimal microgrid, where a predetermined amount of DER is deployed in the system and appropriate network additions are made to meet reliability guarantees in the presence of component unavailabilities. The paper presents a formulation of the optimization problem, its implementation using a method based on particle swarm optimization, and its demonstration on a small distribution system.

Key-Words: microgrid, reliability, optimal distribution planning, distributed energy resources, particle swarm optimization.

1 Introduction

In recent years, distributed energy resources (DER) have been an active area of research as potential alternatives to centralized generation [1] – [3]. With increasing deployment of these resources, which is expected to be at or near centers of utilization or load growth, it is expected that present-day distribution systems will evolve into “microgrids” [1] – [6], which are viewed as networks containing DERs and connected in a grid-like fashion. Much research is being conducted in this area. The largest and most concerted effort consists of the development of the CERTS microgrid concept [4] – [6], which focuses on a self-sustained heat and power supply to a compact cluster of loads. Several research efforts have focused on the problem of sizing and optimal placement of DERs in a distribution network [1] – [3], [7], [8]. These approaches, with the exception of [3], have assumed and have tried to preserve the fundamentally radial structure of the distribution network. On the other hand, our approach [9] – [11] has been to develop microgrids that are networked in structure and conform to the US Department of Energy’s vision of microgrid that can operate in both grid-connected and islanded

modes [12], [13]. Further, our work addresses the problem of distribution network expansion by deploying distributed resources and optimally interconnecting them to satisfy explicit reliability criteria.

The development of optimal microgrid architecture, as envisioned by the authors, consists of two aspects: (a) sizing and siting of DER, and (b) optimal network topology, comprising an optimal set of interconnections and associated capacities. In previous work, the authors have solved these problems independently. In [9] – [11], the topology was optimized assuming predetermined sizing and siting of DERs. In [14], [15], optimal deployment and sizing of generation was performed assuming a given distribution network. Building on the experience and insight gained in solving these problems independently, we determined to attempt the task of developing a unified method for simultaneously optimizing the DER deployment and network configuration, since one is dependent upon the other. The work reported in this paper represents a first step toward developing an integrated solution methodology.

In this paper a scheme for solving the combined reliability-oriented optimal microgrid architecture problem is presented. This scheme is based on

Particle Swarm Optimization (PSO) [16]. The scheme makes use of the “unit-link” concept developed by the authors [9]. This concept was critical in the development of a formulation that accounted for the physical relationships between the variables considered. This paper presents the PSO formulation of the problem and describes the method and the implementation. The method is also demonstrated on a test system.

2 Problem Statement

Let us consider the task of developing a self-sufficient, networked (looped) microgrid from an existing distribution system. The existing system is connected to the main grid at the Point of Common Coupling (PCC). For the purpose of developing this network into a self-sufficient system, it is assumed that the system is disconnected from the utility, i.e., islanded operation is assumed. Under these circumstances, the local load must be met by means of distributed generation. First of all, sufficient generation is required. A reserve margin of 20% of the total load is assumed. Further, it is assumed that the total generation required is already available in the form of a given number of groups (or clusters) of DER units. Then one needs to address the problem of optimal siting of resources. For this, one acquires permission to install generating units, or build DER ‘farms’ or ‘parks’ at various locations. From the available locations, one needs to decide where to finally place the clusters of DER units.

Another aspect of a microgrid is the optimal topology, i.e., among all possible rights of way, which ones should be used to build transmission lines, and once the optimal set of paths are chosen, how much capacity to assign to those paths.

The aggregate of the above component problems constitutes the optimal microgrid architecture. This paper presents a method to determine both the topology and location of DER such that the cost is minimized and at the same time satisfying a global reliability stipulation.

While this is a reasonable approach to defining and solving a practical problem, it is clear that several variations, including alternative and more complex formulations, are possible.

3 System Modeling

Generators: These are modeled as two-state devices. Each generator i is described by its maximum generating capacity G_{max_i} and its forced outage rate FOR_i .

Load: For the purpose of system planning, the load has been assumed to remain constant at the coincident peak.

Transmission Lines: The basic element of the transmission network is the *unit-link* which is a transmission line with the following characteristics:

A *unit-link* connecting a given pair of buses is a line of fixed capacity, fixed cost per unit length, fixed impedance per unit length, and of length corresponding to the right of way between the buses.

Unit-links between different bus pairs will have different lengths, impedances and costs, but same capacity.

A *link* between a given pair of buses can consist of one or more (an integral number of) unit-links connected in parallel between that bus pair. The cost of a link is equal to the total cost of the unit-links that constitute the link plus a fixed cost for installing the link along the corresponding right of way.

Network Model: A linearized network model in the form of DC Load Flow [22] has been used in this work.

4 Problem Formulation

The objective of this work is to determine the least-cost microgrid that satisfies a system-wide reliability requirement. The cost of building the microgrid consists of the following parts:

(a) The cost of the transmission network:

Let

J_i = cost of a unit-link along the i^{th} right of way

u_i = number of unit-links in parallel along the i^{th} right of way

J_{Fi} = fixed cost of installing a link along the i^{th} right of way

= 0 if $u_i = 0$

N_ℓ = number of rights of way for building transmission lines

Then, the cost of the transmission network is given by

$$J_T = \sum_i (J_i \times u_i + J_{Fi}) \quad \forall \quad 1 \leq i \leq N_\ell \quad (1)$$

(b) The cost of deploying distributed resources.

Let

N_g = The number of generator clusters

N_d = The number of nodes where we have the permission to build generator farms

JG_{ij} = The cost of deploying the i^{th} cluster at the j^{th} location

d_i = The node where the i^{th} cluster is to be located

Therefore the cost of deploying the set of DG clusters is given by

$$J_G = \sum_i JG_{id_i} \quad \forall \quad 1 \leq i \leq N_g \quad (2)$$

(c) Other costs such as T&D losses, O&M etc.

The total cost is therefore:

$$J = J_T + J_G + \text{other costs} \quad (3)$$

The aim is therefore, to determine

1. The vector $\mathbf{u} = \langle u_1, u_2, \dots, u_{N_\ell} \rangle$, i.e., the (integral) number of unit links to be allocated along each right of way. This will determine the network topology as well as the optimal capacities of transmission lines. The capacity of a line can be found by multiplying the capacity of a unit link by the number of unit links the line is comprised of. Further, if the solution vector specifies that the number of unit links along any particular right of way to be zero, this simply means no transmission line should be built along that right of way. Therefore, the vector \mathbf{u} determines both the set of interconnections and the line capacities.
2. The vector $\mathbf{d} = \langle d_1, d_2, \dots, d_{N_g} \rangle$, i.e., where should each DER cluster is to be located from the list of all possible locations. Each component of this vector is a number or an index pointing to a particular node.

The vectors \mathbf{u} and \mathbf{d} together specify the solution vector $\mathbf{x} = \langle \mathbf{u}, \mathbf{d} \rangle$. Our aim is to find that solution vector which satisfies the following.

$$\text{Minimize } J = J_T + J_G + \text{other costs}$$

subject to

$$EIR > R_0 \quad (4)$$

where

EIR = global energy index of reliability

R_0 = minimum required reliability

The energy index of reliability, EIR , is defined as the ratio of energy served to total energy demand, and is given by equation (10). This index is determined as described in section 5.3.

5 Solution Strategy

5.1 Particle Swarm Optimization

It is easily seen that the problem at hand is an integer optimization problem. The combinatorics, especially due to the topology part of the problem, makes the problem intractable. Further, different deployment strategies invariably lead to different network topologies.

In order to solve this problem, we use the method of Particle Swarm Optimization in this work. This method was chosen because it has been found to be very fast in solving unconstrained optimization problems. It has also been successfully employed in many engineering (constrained) areas including power systems [17]. In the power systems area, it has particularly been used in distribution state estimation [18], dynamic security analysis [19] and AGC tuning [20].

This technique was developed from studying social behaviour such as the flocking of birds in search of food. Classically, the simulation is performed in a square grid of land which is the solution space. The behaviour of the particles in PSO bears a correspondence with that of the birds. Each particle is a potential solution, representing a point in the solution space. In case of the birds, it represents a position in the area of land. The objective of the birds is to find food, the location of which is unknown to them. This is analogous to the optimum solution to an optimization problem where we seek to find that solution or point which maximizes or minimizes the objective function. At each location, the birds have a sense of distance from the location of food. This corresponds to the value of the objective function. The aim of the birds is to minimize their distance from the location of food. During the search for food, birds would finally converge on to that location where the food is. In terms of PSO,

the final point where the particles settle down is the optimal solution identified by the solution process.

The movement of the particles, is governed by three factors. These are as follows: (1) Inertia: the particles continue to move in the direction in which they were originally moving. (2) Personal Best: each particle remembers the location, which gave the best fitness (or value of objective function) so far. This is known as the personal best, and particles tend to move towards their respective personal bests. (3) Group Best: the group best is the best solution represented by the swarm in any given instant. Each particle tends to move towards the group best.

An interaction of the above three components generates a vector that determines the direction and magnitude of movement for each particle. This is given by the following equations:

$$v[\cdot] \leftarrow \alpha \cdot v[\cdot] + r_1 \cdot c_1 \cdot (pbestx[\cdot] - presentx[\cdot]) + r_2 \cdot c_2 \cdot (pbestx[gbest] - presentx[\cdot]) \quad (5)$$

where

$v[\cdot]$ is a vector of velocities in each direction in an $(N_\ell + N_g)$ -dimensional space where the particles are free to move.

$pbestx[\cdot]$ is the vector of co-ordinates (or the point in the space) which gives the personal best encountered by the particle in its history.

$presentx[\cdot]$ is the present position of the particle.

$pbestx[gbest]$ is the position which gives the best fitness value among all the particles in the group. This is also referred to as the group-best.

r_1 and r_2 are uniformly distributed random numbers between 0 and 1, which account for randomness in the social behavior

c_1 and c_2 are parameters that need to be carefully chosen for each application.

In the above equation, the first term represents the inertia. It helps the particles to move out of local minima. This term is also multiplied by a damping coefficient α ($0 \leq \alpha \leq 1$) so that as the search process proceeds, the impact of the inertia diminishes gradually. This factor is also necessary in order to keep the velocities of the particles from diverging. The second term represents attraction towards the personal best while the third term towards the group best.

The velocities or direction of movement is computed for each particle using the above equation. Then, the following equation is used for each particle to update the position.

$$presentx[\cdot] \leftarrow presentx[\cdot] + v[\cdot] \quad (6)$$

5.2 Application to Microgrid Architecture

The previous sub-section provided a brief description of classical PSO, which is used in unconstrained optimization problems. Engineering problems are constrained in nature. Therefore, techniques must be devised for handling constraints. In the following paragraphs, the various structures of PSO formulation have been described and the above issues have been addressed.

Solution Space: The solution vector comprises of two parts: the transmission network, and the deployment of DG. Both the parts are discrete in nature. The solution space is, therefore, a lattice in $(N_\ell + N_g)$ dimensions.

N_ℓ is the number of rights of way where transmission lines can be built. Each axis in the topology part of the solution (the sub-vector \mathbf{u}) represents the number of unit-links allocated to the corresponding right of way. If the position on a particular axis is zero, this simply means that no transmission line should be built along that right of way. Even though, the final solution would consist of integral number of unit-links, from previous work, the topology part of solution vector used a resolution of $\frac{1}{1000}$ of a unit link [11]. The final solution is reported in multiples of a unit-link.

N_g is the number of generating units. The locations where DG-units can be deployed, are numbered consecutively from 1 to N_d . Each co-ordinate in the N_g sub-vector \mathbf{d} can take a value between 1 and N_d . This value is a numerical representation of where the corresponding generating unit is located.

The $(N_\ell + N_g)$ vector specifies the complete solution vector.

Boundary Conditions: Boundary conditions arise due to the following reasons: (a) Physically, the number of unit links cannot be negative. In order to accommodate this, a fictitious "wall" is assumed along each axis corresponding to the topology part of the solution vector. If the motion of the particles makes them transgress this wall, then the particles bounce back into the positive solution space. (b) Because of the numbering scheme for the locations where DG can

be deployed, the particles cannot go out of the range of allocated indices. Therefore, proceeding as above, walls are constructed at each end point. (c) The minimum reliability requirement poses an important constraint on the solutions. Due to this constraint, the solution can be either feasible or infeasible. Several techniques are used for handling these kinds of constraints. For this work, both feasibility methods and penalty function methods were investigated. The penalty function approach was found to perform better. The construction of the penalty function is described below.

The Modified Objective Function: After including the penalty function, the new cost function now becomes:

$$J = J_T + J_G + \text{other costs} + \phi(\mathbf{x}_i | \mathbf{x}_f) \quad (7)$$

where, $\phi(\mathbf{x}_i | \mathbf{x}_f)$ is the penalty function for the infeasible solution vector \mathbf{x}_i based on the most recent feasible solution \mathbf{x}_f . This is described in detail later in this section.

For any given solution, if the solution is feasible, then the value of the penalty function is zero. If the solution is not feasible, then the penalty depends on two factors:

1. How far the last known feasible solution was from the boundary.
2. How far the current infeasible solution is from the boundary.

This is illustrated below.

Let the particle move from a feasible solution to an infeasible solution. Let the feasible solution be denoted by the vector \mathbf{x}_1 and the infeasible solution by \mathbf{x}_2 . Because of this movement, the particle has crossed the boundary of the feasible space. The boundary is represented by

$$EIR = R_0 \quad (8)$$

where R_0 is the minimum reliability required.

Let the *EIR* indices for the solutions \mathbf{x}_1 and \mathbf{x}_2 be R_1 and R_2 respectively and the costs J_1 and J_2 respectively. Now, the cost of the infeasible solution must be raised by imposing a suitable penalty. This penalty is calculated using the following equation:

$$\phi(\mathbf{x}_2 | \mathbf{x}_1) = 2 \times \left(\frac{R_0 - R_2}{R_1 - R_2} \right) \times |J_1 - J_2| \quad (9)$$

Essentially, this equation penalizes the infeasible solution in ratio of the distances of the feasible and infeasible solutions from the boundary R_0 .

Further, let us assume that the particle moves to another *infeasible* solution \mathbf{x}_3 in the next step. In this case, the penalty will be calculated in proportion to the last known feasible solution i.e., \mathbf{x}_1 . If \mathbf{x}_3 were a feasible solution, then this would serve as the last known feasible solution for the subsequent transitions to infeasible solutions.

Number of particles: The choice of number of particles depends on many factors. If there are very few particles, then the solution space would not be adequately covered. In case of problems with many local minima, the simulation would converge quickly to one of these and terminate prematurely. On the other hand, if the number of particles is large, then initializing the particles to the feasible space becomes difficult. For this application, a number of particles equal to the number of nodes in the system was found to perform well.

PSO parameters: Values of parameters α , c_1 and c_2 were determined after trial and error. The values used are reported in the ‘‘Demonstration’’ section.

5.3 Reliability Evaluation

In a distribution network, a measure of reliability based on the energy supplied is more appropriate. Therefore, an energy index of reliability (*EIR*) is chosen as the index to be specified. The *EIR* is obtained as follows: first the expected minimum curtailment is obtained by evaluating upto second order generation and significant third order generation contingencies along with first order transmission line contingencies. The expected minimum curtailment divided by the total demand gives the energy index of unreliability, which subtracted from unity yields the *EIR*.

As mentioned before, a linearized power flow model has been used to determine the minimum curtailment for any given contingency. This is implemented in the form of a Linear Programming problem [22]. The reliability evaluation is described in detail in [9] – [11].

The reliability of the network is given by [10]:

$$EIR = 1 - \frac{EPNS}{D_T} \quad (10)$$

where

EIR = Energy Index of Reliability
EPNS = Expected Power Not Served
D_T = Total Power Demand.

5.4 Algorithm

At the beginning of the solution process, the particles are initialized to the feasible space. This is necessary otherwise the penalty for the initial solution cannot be computed meaningfully. After initialization, at each subsequent iteration, the objective values for each particle is computed. Also, the respective *EIRs* are also computed. Based on feasibility or infeasibility of the current solution, a penalty factor is imposed on the cost of the solution. After this, the group best is identified and personal bests are updated as necessary. Also, the last known feasible solution for each particle is updated as necessary. The velocities and next positions are computed using equations (5) and (6).

At each iteration, the best feasible solution obtained so far is kept track of. The process is continued until a maximum number of iterations has been reached or the coefficient of variation of the cost of the best feasible solution falls below a given threshold

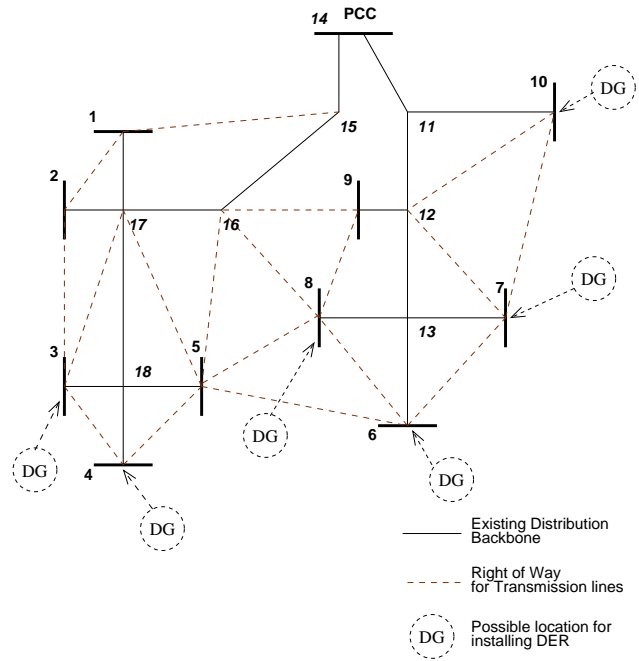


Figure 1: Test system

6 Demonstration

The method was applied to the system shown in Fig. 1. The available rights of way for building new distribution lines are shown as dashed lines. The paths along the existing distribution system, shown as solid lines, are automatically available as rights of way. The locations where DERs can be sited are shown as dashed circles. The capacity of a unit-link was taken to be 0.1 MW, and reactance = 0.006 p.u. per mile.

For the purpose of demonstration, the cost of a unit-link was assumed to be proportional to the length of the corresponding right of way. Further, fixed costs were assumed as follows. For rights of way corresponding to the existing distribution network, fixed costs were assumed to be 10% of the cost of the corresponding unit link. For new rights of way, fixed costs were assumed to be 25% of the cost of the corresponding unit link. The cost of deploying DER at the respective locations was assumed to be zero. Also, other costs were not used in this demonstration.

In this system, Buses 1 to 10 are load buses. The load data is given below in Table 1. The data shown in the table represents a predicted load growth, which must be met by deploying distributed generation.

Generation data is given in Table 2.

The PSO was run with the following parameters:

$$\alpha = 0.80, c_1 = 1.5, c_2 = 1.5.$$

Number of particles = 18

Table 1: Load Data for Test System

Bus	Load (MW)	Bus	Load (MW)
1	0.7291	2	0.7291
3	0.9167	4	0.9167
5	0.8668	6	0.7500
7	0.7500	8	0.8668
9	0.8668	10	0.9167

Maximum number of iterations = 20000

Minimum coefficient of variation = 0.001

Target reliability: *EIR* = 0.99

The resulting microgrid is shown in Fig. 2. The newly added transmission lines are shown as arcs. The locations where the DER clusters should be placed are also shown. The capacities of the transmission lines are tabulated below in Table 3. The optimal DG deployment strategy is: Cluster 1 at Bus 3, Cluster 2 at bus 10 and Cluster 3 at bus 7.

7 Discussion

From the results we observe that the network is significantly looped. Further, some of the line segments in the original backbone network have been reinforced. This is because of the anticipated load growth factor. Most of the lines near the generating nodes have been strengthened, while upstream feeder segments are not.

Table 2: Generation Data for Test System

Cluster No.	Number of units	Capacity (MW) of each unit	FOR
1	7	0.50	0.10
2	6	0.50	0.05
3	7	0.50	0.10

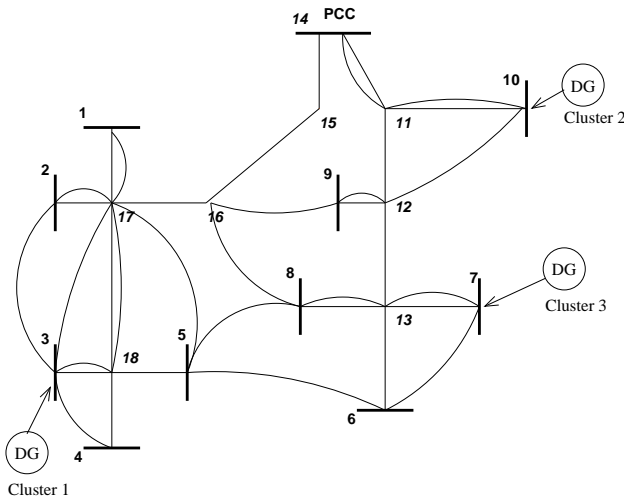


Figure 2: Resulting Microgrid of the Test System

This is because, as we move upstream, the capacity of the segments increase. The PSO method recognizes the surplus capacity (because now we are trying to push power in the opposite direction) and makes use of it. From Fig. 2 we can see that most of the newly added lines cluster around the left radial section of the original distribution network. This can be attributed to the comparatively larger loads on this part of the network. Further, due to transmission line contingencies, additional transmission infrastructure must be built around the heavily loaded sections, so that the impact to the expected unserved energy is minimized.

An important factor that governs the network topol-

Table 3: Results: Optimal Topology

Line	Cap (MW)	Line	Cap (MW)	Line	Cap (MW)
2-3	0.5	5-8	0.1	8-16	0.1
3-4	0.9	5-6	0.1	10-12	0.4
5-17	0.1	6-7	0.6	1-17	0.2
3-17	0.2	9-16	0.1	2-17	0.2
17-18	0.1	3-18	0.3	11-14	0.2
10-11	0.7	9-12	0.4	8-13	0.3
7-13	0.9				

ogy is the fixed costs associated with installing along new rights of way. If those costs are significantly high, then the algorithm would find a better solution by strengthening segments of the backbone network connecting a pair of nodes, rather than directly connecting the nodes along a new right of way.

Consideration of losses and other costs would affect the results. However, the purpose of this paper is to present a rational methodology for optimal microgrid architecture, rather than to emphasize the results obtained.

8 Conclusion

This paper presented a formulation of the problem of developing reliability stipulated optimal microgrid architectures, and a solution technique based on particle swarm optimization. The method simultaneously optimizes the network configuration and the location of DERs.

The method was demonstrated by applying it to a test system. Useful insights were gained from the experience. Further work will consist of developing improved and expanded formulations of the problem, and of determining suitable solution techniques. Expanded formulations to be explored will include optimal sizing of DER, and incorporating reliability differentiated services.

In this paper, a rational approach to solving a practical problem was presented. It is possible to develop alternative formulations to the problem, and these variations provide the opportunity for interesting and insightful research and development in the area of microgrid architecture. Further work in this area will be reported in due course.

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