

Reliability Stipulated Microgrid Architecture Using Particle Swarm Optimization

Joydeep Mitra
Klipsch School of Electrical and
Computer Engineering
New Mexico State University
Las Cruces, New Mexico 88003
Email: jmitra@nmsu.edu

Shashi B. Patra
Klipsch School of Electrical and
Computer Engineering
New Mexico State University
Las Cruces, New Mexico 88003
Email: patra@nmsu.edu

Satish J. Ranade
Klipsch School of Electrical and
Computer Engineering
New Mexico State University
Las Cruces, New Mexico 88003
Email: sranade@nmsu.edu

Abstract—Distributed energy resources have been receiving increasing attention over the past decade as alternatives to centralized generation. In the next few decades, the penetration of microgrids is expected to grow dramatically. The bulk of DERs will be integrated into existing distribution systems. To maximize the economic and reliability benefits of these installations, distributed systems will evolve into networked ‘microgrids’.

This paper describes a rational method of developing microgrid architectures in a manner that maximizes the economic benefits of deploying the resources. The method consists of a particle swarm optimization (PSO) formulation that seeks to make the most economical connections that will satisfy the stipulated reliability criteria. This paper describes the method and its implementation, and illustrates it by means of examples. The validation of the method using a rigorous dynamic programming approach, is also outlined.

I. INTRODUCTION

Distributed Energy Resources (DER) have been an important area of research during the last decade. This field has been receiving increasing attention largely as potential alternatives to centralized generation [1] – [3]. This is partly due to the advantages of DER, namely, modularity, compact size, portability, lower emission and sometimes higher conversion efficiency, and lower costs and losses in transmission and distribution (T&D); and partly because they are an expedient alternative to the expansion and upgrade of T&D which is expensive and time consuming. It is anticipated that the potential use of DERs and their subsequent penetration into the distribution network will grow dramatically. Specifically, the bulk of the DERs will be integrated into existing distribution systems. In order to effectively exploit the economic benefits of these installations, distribution systems that have been operating in a radial structure will evolve into a grid-like operation. They will evolve into networked microgrids.

In the areas of transmission expansion planning [4] and developing microgrids [1] – [3], [5] – [6], significant research has been conducted. Many operational aspects of microgrids have also been addressed [7] – [9]. The contribution of CERTS to this area is also noteworthy [5] – [7]. The “CERTS Microgrid Concept” focuses on a self-sustained heat and power supply to a compact cluster of loads. Many approaches have focussed on the issue of optimal placement of DERs in a distribution

network [1] – [3]. 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 [10], [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 issue of distribution network expansion with explicit reliability criterion by deploying distributed resources.

In [10], [11], an analytical method based on Dynamic Programming (DP) to solve the problem of developing optimal microgrid architectures has been presented. The DP based technique along with the concept of the “unit-link” was used to determine the optimal set of interconnections between load and generation nodes in a distribution network. The method, though rigorous, was found to be computationally intensive. In particular, solving a network consisting of 22 nodes took time in the order of days on a BeoWulf cluster. This motivated the authors to devise a heuristic approach to solve the problem.

Heuristic methods such as Genetic Algorithms (GA), Simulated Annealing and Particle Swarm Optimization (PSO) [14] have been used in many engineering areas including power systems. Of these, PSO has emerged as a powerful and versatile tool because of the simplicity of the algorithm. The algorithm is very fast as it employs only primitive operators on potential solutions. Further, in this technique, the potential solutions interact with only one solution, rather than interacting with every other solution as in other methods such as GA. PSO has been successfully applied to many areas in power systems [15] like distribution state estimation [16], dynamic security analysis [17] and AGC tuning [18].

In this paper, a scheme for solving the reliability-oriented optimal microgrid architecture problem is presented. The scheme makes use of the “unit-link ” concept developed by the authors. This paper presents the PSO formulation of the problem and describes the method and the implementation. Also, the method has been applied to two test cases and the results have been validated using results obtained from the DP-based method.

II. SYSTEM MODELING

Generators: These are modeled as two-state devices. Each generator i is described by its maximum generating capacity G_{max} 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 the link is equal to the total cost of the unit-links that constitute the link.

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

III. PROBLEM FORMULATION

This work aims at determining the optimal network configuration which satisfies a specified global reliability requirement and a locational reliability guarantee. Mathematically, this problem can be posed as follows.

Minimize

$$J = \sum_{i,j} J_{ij} \times x_{ij} \quad \forall 1 \leq i < j \leq N_n \quad (1)$$

subject to

$$EIR > R_0 \quad (2)$$

where

- J = cost of the transmission network
- J_{ij} = cost of a unit-link between nodes i and j
- x_{ij} = number of unit-links in parallel between nodes i and j
- N_n = number of nodes in the system
- EIR = global energy index of reliability
- R_0 = minimum required reliability.

Equation (1) assumes that each possible path between the nodes of the system is available as a right of way. In general, this may not be true. In such a case (1) may be rewritten as:

$$J = \sum_{i=1}^{N_\ell} J_i \times x_i \quad (3)$$

where

- J_i = cost of a unit-link for the i th right of way

- x_i = number of unit-links in parallel in the i th right of way
- N_ℓ = number of rights of way

The following sections describe the PSO formulation, the method and results.

IV. SOLUTION STRATEGY

A. The Particle Swarm Optimization Technique

The PSO technique employs swarm intelligence to identify the solution to an optimization problem. This method was developed from simulating social behavior such as the flocking of birds in search of food. In terms of birds in search of food, the simulation is performed on a square grid of land. This area is the solution space. The behavior of particles in PSO is analogous to that of birds. Each particle represents a potential solution which is a point in the solution space, or as a position in the square area of land, in case of the birds analogy. The birds fly in search of food. The location of food is analogous to the optimum solution to the problem. Each bird, given its present position, has a sense of distance from the food. This is analogous to the “objective value” of the corresponding optimization problem. The aim of the birds is to converge or narrow down on that location where the food is, or in other words minimize the distance from the location of the food. The final location where the birds settle down is the optimal solution identified by the solution process.

During the process, the motion of the particles is governed by three factors. These are as follows. (1) Inertia: the particles tend to move in the direction in which they were originally moving. (2) Personal Best: each particle remembers its history. In particular, it remembers that location that gave the best estimate of objective function. This location (or solution) is known as the personal best for that particle. Each particle tends to move towards its own personal best. (3) Group Best: Each particle tends to move towards the group best. The group best position is the best solution represented by the swarm in any given time step. An interaction of the above three components generates a direction of movement corresponding to each particle for the next time step. In the next time step, the particles move in the direction of their movement. The equations governing the movement of any particle are shown below:

$$v[\cdot] \leftarrow \alpha \cdot v[\cdot] + \text{rand}() \times c_1 \times (pbestx[\cdot] - presentx[\cdot]) + \text{rand}() \times c_2 \times (pbestx[gbest] - presentx[\cdot]) \quad (4)$$

where

- $v[\cdot]$ is a vector of velocities in each direction in an N_ℓ -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 the particle has encountered so far.
- $presentx[\cdot]$ 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 group-best.

$\text{rand}()$ is a uniformly distributed random number between 0 and 1, which accounts for randomness in the social behavior or bird flocking.
 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. 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.

$$\text{present}x[\cdot] \leftarrow \text{present}x[\cdot] + v[\cdot] \quad (5)$$

B. Application to Microgrid Architecture Optimization

The problem of optimizing microgrid architecture is very distinct from the classical formulation presented above. The problem at hand is a constrained optimization problem. Therefore, techniques must be devised for handling boundary conditions arising from physical constraints and those arising from infeasibility of solutions.

In the following paragraphs the various structures of the PSO formulation have been described and the above issues have been addressed.

Solution Space: The state space is discrete — it is a lattice in N_ℓ dimensions, where N_ℓ is the number of rights of way. Each axis represents a right of way, and a position on that axis represents the number of unit-links allocated to that particular right of way. If the position on a particular axis is zero, this simply means that no transmission should be built along that right of way.

In the DP formulation developed earlier [10], [11], the solutions could take integral multiples of unit links. In particular, because of computational constraints, the solution space of the DP method consisted of unit-links at multiples of 2. This means that along any right of way, the number of unit-links allocated can be multiples of 2.

However, it was found that enforcing the same parameters for the PSO formulations resulted in non-optimal solutions. Therefore, the resolution of the solution space was increased. Again, the state space is still discrete, and the particles still move in multiples of a unit-link, but in case of PSO, the unit link has a higher granularity than that used in the DP method. The other parameters of the unit-link are adjusted accordingly to be consistent with the parameters of unit-link used in DP. In this work, the minimum step length is equal to an equivalent of $\frac{1}{1000}$ times the unit-link used in the DP formulation. This resolution of the solution space was found to perform satisfactorily.

Boundary Conditions: Boundary conditions arise from two reasons: (a) Physically, the number of unit links cannot be

negative. In order to accommodate this, a fictitious “wall” was assumed along each axis. If the motion of the particles made them transgress this wall, then those particles bounce back into the positive state space. (b) Because of minimum reliability requirements, the solutions can be infeasible. Several techniques are used for handling these constraints [19]. For this work both feasibility methods and penalty function methods were investigated. It was found that the performance of a penalty function approach was superior. The construction of the penalty function is described below.

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

$$J = \sum_{i=1}^{N_\ell} J_i \times x_i + \phi(\mathbf{x}) \quad (6)$$

where

$\mathbf{x}$ = the vector $(x_1, x_2, \dots, x_{n_\ell})$ representing a solution
 $\phi(\cdot)$ = the penalty function.

The value of the penalty function is zero if the solution $\mathbf{x}$ is feasible. If the solution is not feasible, then the imposed penalty is computed from 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 the vector $\mathbf{x}_2$. Because of this movement, the particle has crossed the boundary of the feasible space. The boundary is represented by

$$EIR = R_0 \quad (7)$$

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:

$$\phi(\mathbf{x}_2|\mathbf{x}_1) = 2 \times \left(\frac{R_0 - R_2}{R_1 - R_2} \right) \times |J_1 - J_2| \quad (8)$$

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 rights of way was found to perform well.

PSO parameters: Values parameters α , c_1 and c_2 were used after trial and error. The specific values for specific test cases are specified in the results section.

C. 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 first order generation contingencies. The 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. This is implemented in the form of a Linear Programming problem. The aim is to determine a dispatch that minimizes the load curtailment subject to generation availability and network constraints as follows [20]:

$$\text{Loss of Load} = \text{Min} \left(\sum_{i=1}^{N_b} C_i \right) \quad (9)$$

subject to

$$\begin{aligned} \hat{B}\theta + G + C &= D \\ G &\leq G^{max} \\ C &\leq D \\ b\hat{A}\theta &\leq F_f^{max} \\ -b\hat{A}\theta &\leq F_r^{max} \\ G, C &\geq 0 \\ \theta &\text{ unrestricted} \end{aligned} \quad (10)$$

where

- N_b = number of buses
- N_t = number of transmission lines
- C = N_b -vector of bus load curtailments
- C_i = i -th element of C , i.e., unsatisfied demand at bus i
- D = N_b -vector of bus demands
- G^{max} = N_b -vector of available generation at buses
- F_f^{max} = N_t -vector of forward flow capacities of transmission lines
- F_r^{max} = N_t -vector of reverse flow capacities of transmission lines
- G = N_b -vector of dispatched generation at buses
- θ = N_b -vector of bus voltage angles
- b = $N_t \times N_t$ primitive (diagonal) matrix of transmission line susceptances
- $\hat{B}$ = $N_b \times N_b$ augmented node susceptance matrix
- $\hat{A}$ = $N_t \times N_b$ element-node incidence matrix

$\hat{A}$ = $N_t \times N_b$ element-node incidence matrix

Although (10) is a standard representation of the DC flow constraints, it is usually necessary to fix one of the bus angles at zero to be able to obtain a feasible solution. Further, in the process of building the optimal network and while evaluating transmission line contingencies, the microgrid may comprise many islands. It is important to identify these islands and set appropriate reference bus angles in each of these islands.

The above minimization procedure is performed for each contingency.

Let LOL_i be the loss of load obtained for the i^{th} contingency, with a probability of $prob_i$. Then the expected power not served is given by:

$$EPNS = \sum_{i=1}^{N_c} LOL_i \times prob_i \quad (11)$$

where

$EPNS$ = Expected Power Not Served

N_c = Number of contingencies.

The reliability of the network is then given by:

$$EIR = 1 - \frac{EPNS}{D_T} \quad (12)$$

where

EIR = Energy Index of Reliability

D_T = Total Power Demand.

Normally, the *EIR* is computed using the equation:

$$EIR = 1 - \frac{EUE}{E_T} \quad (13)$$

where

EUE = Expected Unserved Energy

E_T = Total Energy Demand.

Equation (13) becomes equivalent to (12) when the demand is constant over the period of interest. While this method is amenable to any suitable representation of load, in this work the peak coincident load was used. This was considered appropriate for system planning.

D. Solution Strategy

At the beginning of the solution process, the particles are first 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 (4) and (5).

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.

V. DEMONSTRATION: CASE STUDIES AND RESULTS

The optimization was applied to a 22-bus system derived from the distribution network at Bus 2 of the RBTS [21]. Rights of way between nodes and costs thereof were established from the layout given in the single line diagram. For the purpose of demonstration, the cost of interconnecting nodes i and j was assumed to be proportional to the distance as shown in the layout.

The location and size of the generating units were assumed to be known *a priori*. Typical values of forced outage rates were assumed. For system planning purposes the load was assumed to be at the coincident peak at the buses.

The capacity of each unit-link was taken to be 0.1 MW with impedance 0.006 p.u. per mile. However, the resolution of solution space for the PSO method was increased by discretizing it at where step length equivalent to $\frac{1}{1000}$ of the above mentioned unit link. This granularity was necessary in order to obtain results comparable to those obtained from the DP-based method.

The following values of the PSO parameters were used:

$$\begin{aligned}\alpha &= 0.75 \\ c_1 &= 1.0 \\ c_2 &= 1.5\end{aligned}$$

The program was executed with a setting of maximum *EPNS* of 4% of the total demand which is equivalent to $EIR \geq 0.96$.

The method was applied to two situations: (1) In the first case a microgrid was built from ground-up. The locations of load and generation along with costs associated with rights of way were assumed. (2) In reality, it is more likely that a microgrid would evolve as an expansion of an existing distribution network. Therefore a second case study was performed. Our method was applied to an existing distribution backbone. A load growth was assumed along with added generation. Then, a microgrid was developed from that network.

For the first case, only the main buses of the RBTS, i.e., the load buses have been considered. The nodes arising from the points where feeder segments met were not used in the analysis. Those nodes were eliminated because the microgrid was supposed to be built from scratch and hence, from the point of view of the analysis, the distribution backbone did not exist and neither did the “intermediate” nodes. In the second case, these nodes were duly considered.

In both the cases a worst case scenario was analyzed where there is no assistance from the grid and the load is at the coincident system peak. The cases and the results are described in detail below.

A. Building a Microgrid from Scratch

In this analysis all the lines from the above network were removed because of the reasons mentioned in the previous section. The loads were taken to be the peak loads at the respective buses. The generation and load data is provided below in Table I and Table II respectively.

TABLE I
GENERATION DATA FOR SYSTEM IN CASE A

Bus	Gen (MW)	FOR
1	5.0	0.06
5	10.0	0.10
10	3.5	0.08
11	5.0	0.10
22	7.5	0.10

TABLE II
LOAD DATA FOR SYSTEM IN CASE A

Bus	Load (MW)	Bus	Load (MW)	Bus	Load (MW)
1	0.8668	9	1.8721	16	0.7500
2	0.8668	10	0.8668	17	0.7291
3	0.8668	11	0.8668	18	0.7291
4	0.9167	12	0.7291	19	0.7291
5	0.9167	13	0.9167	20	0.9167
6	0.7500	14	0.9167	21	0.9167
7	0.7500	15	0.7500	22	0.7500
8	1.6279				

The resulting network is shown in Fig. 1. The network configuration is tabulated in Table III.

TABLE III
CASE A RESULTS: OPTIMAL MICROGRID BUILT FROM SCRATCH

LINE	Cap (MW)	LINE	Cap (MW)	LINE	Cap (MW)
1-18	1.04	11-12	0.73	21-22	2.05
1-2	0.87	5-6	0.75	10-16	0.90
4-5	0.92	5-7	0.75	8-11	1.84
15-22	0.24	1-19	1.35	16-17	0.94
3-5	0.87	15-21	0.54	17-22	0.33
19-20	0.61	1-16	0.68	10-21	0.74
8-9	0.25	10-14	0.94	11-16	0.84
10-13	0.92	18-20	0.32	8-10	0.16
5-9	1.51	5-19	0.01	9-11	0.39
5-16	0.79	11-14	0.12		

B. Expansion of an Existing Distribution System into a Microgrid

In this case, the original backbone network was retained and used as a starting point for determining the architecture of the microgrid. The line capacities were assumed to be at 150% of their base loading.

This analysis is different from the previous one in the following respects: a load growth of 100% was assumed. So, the new loads at the buses are twice the values shown in Table II. Correspondingly generation was increased. The new generating capacities are tabulated in Table IV. Again, the reliability criterion of $EIR \geq 0.96$ was used.

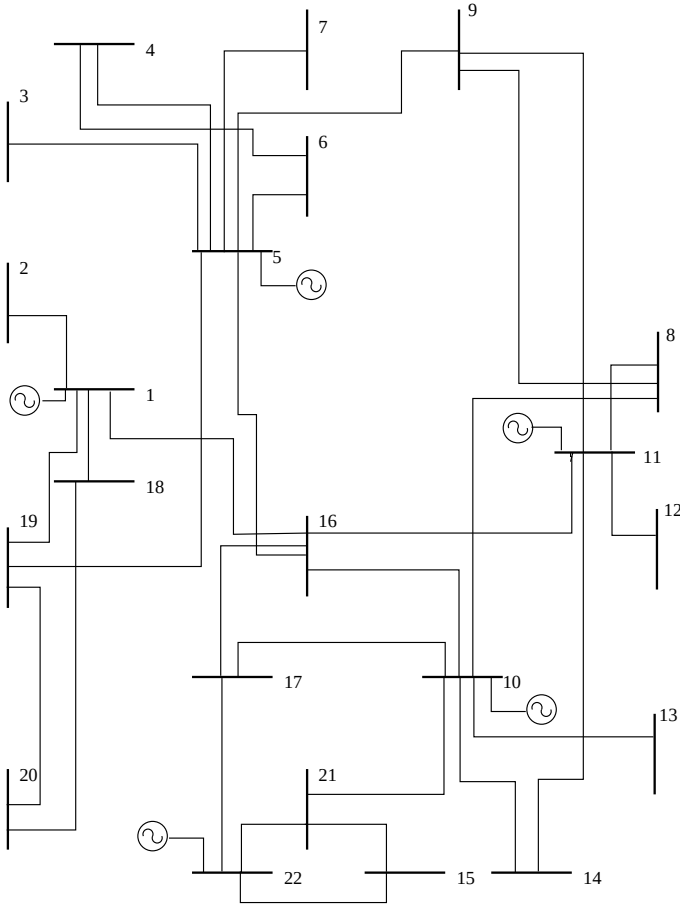


Fig. 1. Case A Topology: Optimal microgrid built from scratch.

The resulting microgrid is shown in Fig. 2. In this figure, the original backbone network is shown in straight lines, while the lines added by the algorithm are shown as arcs. The new lines that were added and their capacities are tabulated in Table V.

TABLE IV
GENERATION DATA FOR SYSTEM OF CASE B

Bus	Gen (MW)	FOR
1	7.5	0.06
5	20.0	0.10
10	10.0	0.08
11	10.0	0.10
22	15.0	0.10

C. Validation of Results and Discussion

The costs of the networks obtained both from the DP-based method and the PSO method are tabulated below in Table VI.

The time taken by the DP-based method for solving the optimizing the above network was in the order of days, and that too using a BeoWulf Cluster. On the other hand, the PSO method converged in a matter of few hours on a stand-alone workstation. At the same time, the optimal costs reported by the methods are very close. It is significant that the results produced by the PSO method have been thus validated by a rigorous method like DP.

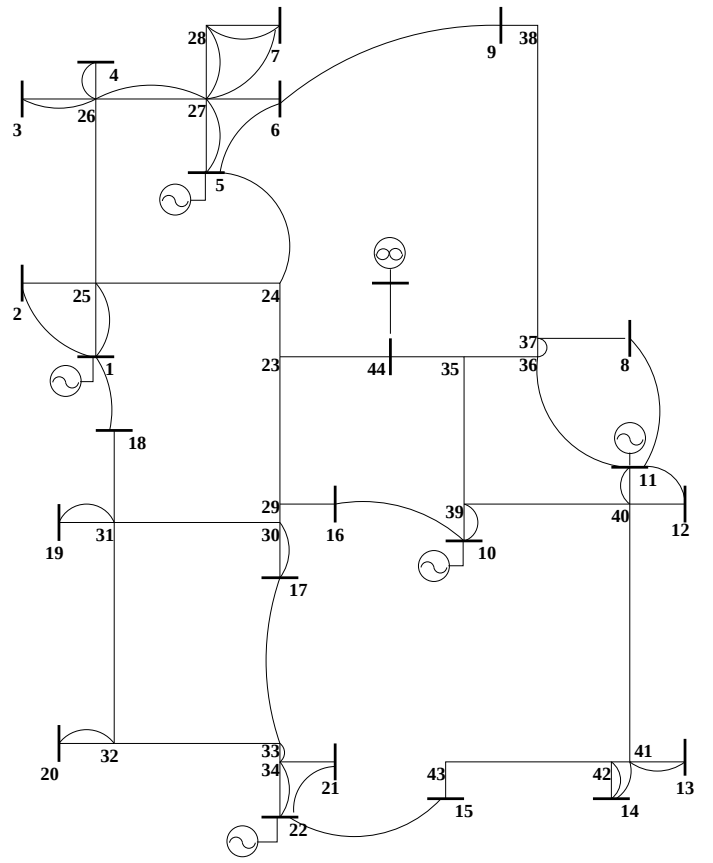


Fig. 2. Case B topology: Optimal microgrid developed from an existing distribution network.

TABLE V
CASE B RESULTS: OPTIMAL MICROGRID DEVELOPED FROM AN
EXISTING DISTRIBUTION NETWORK

LINE	Cap (MW)	LINE	Cap (MW)	LINE	Cap (MW)
33-34	0.99	26-4	0.43	39-10	4.00
42-14	0.50	30-17	0.24	31-19	0.26
32-20	0.43	34-22	1.97	41-13	0.43
25-1	1.85	26-3	0.33	27-5	3.14
40-11	2.65	11-12	1.20	11-36	2.78
22-15	2.11	27-28	0.43	28-7	0.93
1-2	0.90	5-24	1.79	5-6	1.91
6-9	4.72	7-27	0.19	1-18	2.29
17-33	0.24	14-41	0.11	21-22	1.24
10-16	2.44	11-8	1.92		

Another thing to note is that for Case A, PSO produced a cheaper network than DP. This can be attributed to the resolution of the search space. The DP based method used solution space having a resolution equivalent to 2 unit-links (decreasing this had the effect of increasing the search space and therefore the computation time). The PSO method used a resolution of $\frac{1}{1000}$ of a unit-link, and in this method the computation time proved to be indifferent to the granularity of the search space.

In summary, the PSO method is comparable in accuracy to the DP method, but significantly faster. The resolution of

TABLE VI

COST COMPARISON OF SOLUTIONS OBTAINED FROM DP AND PSO

Case	DP cost	PSO cost	Deviation
A	614.53	597.33	-2.8%
B	459.68	486.02	+5.7%

the search space plays a significant role on the optimality of the solutions. Ideally, DP should produce the most optimal solution, but in order to do this, the resolution must be very small. However, this cannot be done without making the problem intractable even for small problems. For larger problems, this issue becomes more pronounced. On the other hand, the step-length in case of PSO can be made as small as possible without significantly affecting the solution time.

VI. CONCLUSION

This paper presented a method based on PSO to solve the problem of developing reliability stipulated optimal microgrid architectures. The solution was obtained with the help of the “unit-link” concept developed by the authors in earlier work. Issue arising from boundary conditions were addressed by using a penalty function approach.

The method was applied to two test cases, (1) building a microgrid from scratch, and (2) building a microgrid from an existing distribution backbone. In each case, the results were validated using results obtained from a Dynamic Programming based method previously developed by the authors. It was found that PSO produced results comparable to that of DP.

Further work that remains to be completed is to refine the method to achieve more aggressive optimization, both in terms of quality of solution, and in terms of solution time. Also, the formulation will be expanded to accommodate reliability differentiated services and a larger set of contingencies.

ACKNOWLEDGMENT

The work reported in this paper was supported in part by the National Science Foundation, under grant ECS-0410092, and by the Electric Utility Management Program.

REFERENCES

- [1] G. Celli and F. Pilo, “Optimal distributed generation allocation in MV distribution networks,” in *Proc. 22nd IEEE PES Int’l Conf. Power Industry Computer Appl. PICA 2001*, 20-24 May 2001, Sydney, Australia, pp. 81-86.
- [2] A. R. Wallace and G. P. Harrison, “Planning for optimal accommodation of dispersed generation in distribution networks,” in *Proc. 17th Int’l Conf. Electricity Distribution, CIRED 2003*, 12-15 May 2003, Barcelona, Spain.
- [3] N. S. Rau and Y. H. Wan, “Optimum location of resources in distributed planning,” *IEEE Trans. Power Systems*, vol. 9, no. 4, pp. 2014-2020, Nov. 1994.
- [4] G. Latorre, R. D. Cruz, J. M. Areiza and A. Villegas, “Classification of publications and models on transmission expansion planning,” *IEEE Trans. Power Systems*, vol. 18, no. 2, pp. 938-946, May 2003.
- [5] R. Lasseter, A. Akhil, C. Marnay, J. Stephens, J. Dagle, R. Guttromson, A. Meliopoulos, R. Yinger, and J. Eto, “Integration of distributed energy resources: the CERTS MicroGrid concept,” Consortium for Electric Reliability Technology Solutions, Report No. LBNL-50829, Apr. 2002.
- [6] C. Marnay and O. Bailey, “The CERTS MicroGrid and the future of the macrogrid,” Consortium for Electric Reliability Technology Solutions, Report No. LBNL-55281, Aug. 2004.

- [7] John Stevens, “Development of sources and a testbed for CERTS Microgrid testing,” in *Proc. PES General Meeting 2004*.
- [8] Carlos A. Hernandez-Aramburo, Tim C. Green and Nicolas Mugniot, “Fuel consumption minimization of a Microgrid,” in *IEEE Trans. Industry Applications*, vol. 41, no. 3, pp 2063-2068.
- [9] Yunwei Li, Mahinda Vilathgamuwa and Poh Chiang Loh, “Microgrid power quality enhancement using a three-phase four-wire grid-interfacing compensator” in *IEEE Trans. Industry Applications*, vol. 41, no. 6, pp 1707-1719.
- [10] S. B. Patra, J. Mitra, S. J. Ranade, “Microgrid Architecture: A Reliability Constrained Approach,” in *Proc. IEEE Power Engineering Soc. General Meeting 2005*, 12-16 June 2005, San Francisco, CA.
- [11] J. Mitra, S. B. Patra, S. J. Ranade, “A Dynamic Programming Based Method for Developing Optimal Microgrid Architectures,” in *Proc. 15th Power Systems Computational Conf.*, 22-26 Aug. 2005, Liege, Belgium.
- [12] U. S. Department of Energy, *Strategic Plan for Distributed Energy Resources*, Sept. 2000.
- [13] U. S. Department of Energy, *Transmission Reliability Multi-Year Program Plan FY2001-2005*, July 2001.
- [14] J. Kennedy and R. Eberhart, “Particle swarm optimization,” in *Proc. IEEE Intl. Conf. on Neural Networks*, 27 Nov. - 01 Dec. 1995, pp 1942-1948.
- [15] V. Miranda and N. Fonseca, “EPSO-evolutionary particle swarm optimization, a new algorithm with applications in power systems,” in *Proc. IEEE/PES Trans. dist. Conf. and Exhibition 2002*, vol. 2, pp. 745-750.
- [16] S. Naka, T. Genji, T. Yura and Y. Fukuyama, “A hybrid particle swarm optimization for distribution state estimation,” in *IEEE Trans. Power Systems*, vol.18, no. 1, pp. 60-68.
- [17] I. N. Kassabalidis, M. A. El-Sharkawi, R. J. Marks II, L. S. Moulin, A. P. Alves da Silva, “Dynamic security border identification using enhanced particle swarm optimization” in *IEEE Trans. Power Systems*, vol.17, no. 3, pp. 723-729.
- [18] Y. L. Abdel-Magid, M. A. Abido, “AGC tuning of interconnected reheat thermal systems with particle swarm optimizer” in *Proc 10th IEEE Intl. Conf. on Electronics, Circuits and Systems*, 2003, vol. 1, pp. 376-379.
- [19] J. H. Kim and H. Myung, “Evolutionary programming techniques for constrained optimization problems” in *IEEE Trans. on Evolutionary Computations*, vol. 1, no. 2.
- [20] C. Singh and J. Mitra, “Composite System Reliability Evaluation Using State Space Pruning,” *IEEE Trans. Power Systems*, vol. 12, no. 1, pp. 471-479, Feb. 1997.
- [21] R. N. Allan, R. Billinton, I. Sjarief, L. Goel and K. S. So, “A Reliability Test System for Educational Purposes — Basic Distribution System Data and Results,” *IEEE Trans. Power Systems*, vol. 6, no. 2, May 1991.

BIOGRAPHIES

Joydeep Mitra (S ’94, M ’97, SM ’02) received his B.Tech. from Indian Institute of Technology, Kharagpur, and his Ph.D. from Texas A&M University, College Station. He is currently Associate Professor of Electrical Engineering and Associate Director of the Electric Utility Management Program at New Mexico State University, Las Cruces. Dr. Mitra is a Senior Member of the IEEE, and recipient of an NSF Career Award. His research interests include power system reliability, distributed energy resources, and power system planning. (email: jmitra@nmsu.edu)

Shashi B. Patra (S ’02) completed his B.Tech. in EE in the year 2002 from Indian Institute of Technology, Kharagpur, India. Currently he is pursuing a doctoral degree in EE at New Mexico State University. His research interests include power system reliability, network configuration and optimization, distributed energy resources, and computer applications in power systems. (email: patra@nmsu.edu)

Satish J. Ranade (SM) received his B.E. degree from the Indian Institute of Science, MSEE from New Mexico State University and the Ph. D. degree from the University of Florida. He is the PNM Chair Professor in Utility Management in the Klipsch School of Electrical and Computer Engineering, New Mexico State University, and Director of the Electric Utility Management Program. His interests are in power system modeling, simulation and control. (email: sranade@nmsu.edu)