

# A Probabilistic Search Method for Optimal Resource Deployment in a Microgrid

Joydeep Mitra, Mallikarjuna R. Vallem and Shashi B. Patra

**Abstract**—The benefits of distributed energy resources (DERs) can be exploited by developing cost efficient deployment strategies. System planning based on stipulated reliability criteria leads to robust architectures which can meet the consumers' requirements. This paper presents a method for determining siting, sizing and optimal mix of resources from the available types of DER in a microgrid. The method recognizes the impact of Combined Heat and Power (CHP) to meet the thermal load. The paper presents a dynamic programming formulation and demonstrates its application on a six bus test system.

**Index Terms**—Optimal resource mix, distributed energy resources, energy index of reliability

## I. INTRODUCTION

Today's power system operates under a lot of stress. This is due not only to increasing demand, but also because very little investment has occurred in transmission and distribution (T&D) over the last three decades or so. Deregulation of the industry has added to the challenges of operating the system in a reliable manner. There has been an increased necessity for developing systems where reliability is a dominant factor.

Distributed energy resources (DER) have proved to be a potential alternative to conventional generation due to the ease of deployment and also because they enable the postponement of T&D upgrade [1]. Federal support in the form of subsidies [2] and research in material sciences has shown a reduction in the cost of DER technologies in recent years. Combined heat and power (CHP) production is an added benefit [3] of DERs, and the use of CHP can increase the overall efficiency of the system. Moreover most DERs are environmentally clean, saving the added costs of pollution control schemes. With all these benefits from DERs their penetration into the grid will increase. So there is a need to investigate cost efficient strategies to deploy DERs with a sense of reliability.

Our vision of microgrids is that they not only network DGs with load points, but should also have the ability to operate in both grid-connected and islanded modes. Reliability is a measure of the system's capability to serve the demand. There are various indices which quantify the reliability of a distribution system, such as Loss of Load

Probability (LOLP) [4], Expected Unserved Energy, System Average Interruption Duration Index (SAIDI) [5], System Average Interruption Frequency Index (SAIFI), Energy Index of Reliability (EIR) [6]. Reliability study of a system exposes the vulnerable areas of the system. Consumers might have differentiated reliability requirements. So a comprehensive planning strategy based on reliability is necessary to make the system robust.

Deployment of DER differs from that of conventional generation. Various types of DER are available, such as microturbines, fuel cells, photovoltaic, wind, batteries, etc. Based on the type of DER, system planning can vary to maximize the benefits from the options available. For example, solar panels become more viable in places where there is more insolation. Microturbines and fuel cells have CHP which could be used at places where more heat is required. Storage devices are appropriate for peak-shaving applications. In view of the different characteristics of DER technologies it becomes extremely important to build an optimal strategy for deploying such units within a microgrid.

The problem of siting and sizing of DERs has been addressed in various references cited. Ref. [14] describes a successive elimination algorithm to site and size the DERs. Ref. [15] describes a heuristic approach based on cost benefit analysis to optimally determine the capacity and location of the DER from the prospect of a distribution company. Ref. [16] has used a Mixed Integer Programming (MIP) formulation, with branch and bound optimization for an industrial power plant. Ref. [17] deals with a genetic algorithm optimization for deploying a DER resource in a distribution system. Ref. [18] computes capacity based on risk factor and addresses about the reliability issues which arise as a consequence of transmission bottlenecks. In a prior research effort [13] we developed and implemented a method to determine optimal DER sizes and locations using the simulated annealing technique.

This paper presents a formulation based on dynamic programming to optimally size and site DER units as well as determine the optimal mix of different DER types. The proposed method solves the above problem considering an explicit reliability criterion. This paper describes the method and illustrates it by means of an example.

## II. APPROACH

As we are dealing with a microgrid, we assume the operational cost of all the DERs is constant with respect to their location anywhere in the microgrid.

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The energy index of reliability considers the transmission capacities, time varying loads and time varying capacities of the DERs like solar and wind. The cost function has been modeled as a nonlinear programming problem. A dynamic programming (DP) based method has been used to achieve optimal solution.

The problem of resource mix is modeled as a cost optimization problem. The objective function is the total system cost per year. Here the costs taken into consideration are the deployment costs and heat compensation costs. The cost function can accommodate any cost model and any reliability index.

A unit of such DER has an electrical capacity and a thermal capacity. These units of power and heat can be specified depending on those commercially available or feasible. The thermal output is assumed to support the heat loads with direct heating. It becomes the responsibility of the utilities to separate the heat demand from electrical demand so that better planning optimization will be achieved using the CHP mode of the DERs. For DERs like storage, photovoltaics the heat capacity is considered zero.

Different costs like deployment costs, heat compensation costs [13] and fuel costs are incorporated in the cost function. The deployment cost is the cost of deploying a unit of a particular type of DER at a node in the microgrid. For example if the considered microgrid is an urban area, it might cost more to place the DER near the downtown area than to place it at the suburbs. It might cost more to deploy a unit of storage in an open area than in the basement of a hospital. The heat compensation cost takes into consideration the extra cost of the system which has to be spent to supply the excess heat demand which could not be supplied by the heat output of the DERs. Fuel cost is the cost of producing a MWh of energy by the DERs.

### III. PROBLEM FORMULATION

Here the authors used microturbines (MT), photovoltaic (PV), and battery storage (BS) as different types of available resources to be deployed in the microgrid. The formulation is not intended to focus on these three technologies alone; rather, these are treated as representative of the three families of DER, e.g., PV represents the family of time-varying sources such as wind. Microturbines are rated in terms of power capacity and their output power can be controlled. Output from photovoltaics depends on the available insolation and historical data could be used to analyze the time varying capacities. Batteries are rated in terms of both energy and power capacity and can supply power as long as they have stored energy. The physical dimensions of microgrid are so assumed that the insolation variation with time is similar at each node. The microturbines produce heat output which is proportional to the amount of installed capacity.

A unit of DER has a fixed electrical and heat capacity. The PV capacity is the peak electrical capacity, and has no heat output. The unit of BS is measured in kWh, its stored energy capacity. The batteries are considered to deliver a constant power level for 12 hours when completely charged.

BS provides capacity support during peak hours and becomes a load during off-peak time.

Consider a system with  $N_B$  nodes, and  $N_T$  transmission lines. Let  $D_i(t)$  be the hourly load curves for each node.  $G(t)$  is the time variable capacity of the PV arrays. The heat demand is  $H_i(t)$  which is the hourly heat load at  $i^{th}$  node. The number of units of installed generation is  $F$  an ' $n_{bus} \times 3$ ' matrix. The  $i^{th}$  row of ' $F$ ' represents the number of units of MC, PV and BS respectively at the  $i^{th}$  node.

#### A. Modeling of DER Units

The generators are modeled as two state devices for the computation of reliability. Base load time is when the available capacity of MT and PV is sufficient to support the load demand. The total capacity available at a time ' $t$ '

$$G_{tot_i}(t) = P_{unit} \times F(i, 1) + G(t) \times F(i, 2) + G_{storage} \quad (1)$$

where

$P_{unit}$  = Electrical capacity of a unit of MT

$$G_{storage} = \frac{F(i, 3)}{12} \quad (2)$$

in the peak case, since the capacity of storage in kWh is what it can supply for 12 hours.

$$G_{storage} = 0 \quad (3)$$

in the base case.

#### B. Load Modeling

The effective load curve at each node will be the sum of the electrical demand, the heat curtailment and the storage in peak case.

$$TLoad_i(t) = Load_i(t) + HC_i(t) \quad (4)$$

#### C. Deployment Cost

An  $N_B \times 3$  matrix of deployment cost ' $J$ ' is developed such that its  $i^{th}$  element is the cost of deploying a unit of each of MC, PV and BS respectively at the  $i^{th}$  node. A linear depreciation is assumed where annual depreciation rate will be  $r$ . Then the cost for deploying the resource in our system is,

$$r \times J^T \times F \quad (5)$$

where

$r$  = rate of depreciation per year

$F$  =  $N_B$  dimensional solution vector where the  $i^{th}$  element is number of units of DGs at node  $i$ .

$J$  =  $N_B \times 3$  matrix of deployment costs.

#### D. Heat Compensation Cost

If the heat demand at any node is not supplied by the CHP at that node, excess heat demand is compensated by electrical heating. There are other heating options available like gas heating etc. But here the problem is modeled considering the heat curtailment as an additional load at that node. So there is an excess cost to supply the additional heat demand which is proportional to the heat curtailment. The time variable heat demand curve is  $H_i(t)$  at each node  $i$ . The heat curtailment  $C_H$  at each node at a time ' $t$ ' is,

$$C_{H_i}(t) = \{H_i(t) - F_i(1) \times U_H\}^+ \quad (6)$$

where

$H = N_B$  vector of heat demand at the nodes.

$U_H$  = heat output of a unit of DG.

and the superscript '+' denotes the following operations.

The  $i^{th}$  element of the vector  $C_H$  is,

$$\begin{aligned} a^+ &= a & \text{if } a \geq 0 \\ a^+ &= 0 & \text{if } a < 0 \end{aligned}$$

For simplicity we take the units for heat as power units. The additional costs for the heat compensation will be

$$J_{power} \times 365 \times U_N \times \sum_{T=1}^{24} C_H \quad (3)$$

where

$U_N$  = unit vector of dimension  $N_B$ .

$J_{power}$  = cost of gas to produce a unit of heat.

#### E. Fuel Cost

MT needs natural gas as fuel to operate. Fuel cost is the cost of operating MT throughout a year for which the total system cost is computed.

$$J_{power} \times 8760 \times \sum_{N_B} F(i,1) \quad (4)$$

This is the advantage of PV over MT in terms of operating cost. Where as MT have lesser deployment costs than PV.

Mathematically the problem can be expressed as follows.

Minimize

Cost =

$$r \times J^T \times F + J_{power} \times 365 \times U_N \times \sum_{T=1}^{24} C_H(t) + J_{power} \times 8760 \times \sum_{N_B} F(i,1)$$

Subject to:

1) Stipulated reliability criterion:

$$EIR > R_0$$

where

$EIR$  = Energy Index of Reliability

$R_0$  = minimum reliability desired

2) Capacity adequacy:

$$C(t) = 0$$

where

$C$  =  $N_B$  vector of bus power curtailments.

3) Energy adequacy: The energy generating resources are the MT and the PV. So the deployed resource should be able to meet the total energy needs of the system.

$$\frac{1}{24} \{P_{unit} \times 24 \times \sum_{i=1}^{nbus} F(i,1) + G(t) \times \sum_{i=1}^{nbus} F(i,2)\} \geq \frac{1}{24} \left( \sum_{i=1}^{nbus} Tload_i \right)$$

4) Storage capacity adequacy: The deployed storage should be able to store enough energy so that it can provide capacity support to the system during peak load.

$$\frac{F(i,3)}{12} \geq \frac{1}{24} \{P_{unit} \times \sum_{i=1}^{nbus} F(i,1) + G(t) \times \sum_{i=1}^{nbus} F(i,2) - \sum Tload_i\}$$

#### IV. RELIABILITY EVALUATION

The energy index of reliability is defined as the expected load served as a fraction of the total demand. It reflects the transmission adequacy of the system in reliability assessment of a system. In [19]  $EIR$  is computed for peak load. However the time varying loads might change the reserve margin which could not be accounted for if we use only the peak load. Particularly when modeling time varying capacities like PV and wind etc, we need a more comprehensive form of the  $EIR$  of the system. In this work time varying loads and the time variable capacities of the DERs has been duly considered. This section details the reliability evaluation method.

The total generation and the total load available at each node is a function of time. The curtailment at each node is computed for each contingency at each hour using a DC load flow method [6].

$$\text{Loss of Load (t)} = \text{Min.} \left( \sum_{i=1}^{N_{bus}} C_i \right)$$

subject to:

$$\begin{aligned} \hat{B}\theta + G + C &= D(t) \\ G &\leq G_{tot} \\ C &\leq D \\ |b\hat{A}\theta| &\leq F_{max} \end{aligned}$$

$\theta$  unrestricted

where,

$D$  =  $N_B$  vector of bus load

$G_{tot}$  =  $N_B$  vector of available generation at buses

$F_{max}$  =  $N_T$  vector of flow capacities of transmission lines

$b$  =  $N_T \times N_T$  primitive (diagonal) matrix of transmission line susceptances.

$\hat{A}$  =  $N_T \times N_B$  element-node incidence matrix.

$\hat{B}$  =  $N_B \times N_B$  augmented node susceptance matrix.  
=  $\hat{A}^T b \hat{A}$ .

$\theta$  =  $N_B$  vector of bus voltage angles.

Then for each hour 't' an expected part of load not served is evaluated.

$$EPNS(t) = \sum_{i=1}^{N_C} LOL_i(t) \times prob_i$$

where

$EPNS$  = expected power not served.

$N_C$  = number of contingencies.

The total expected unserved energy ( $EUE$ ) for 24 hours is then added up for the whole day.

$$EUE = \sum_{i=1}^{24} EPNS(t)$$

The Energy index is computed as

$$EIR = 1 - \frac{EUE}{\sum_{t=1}^{24} D_{Tot}(t)}$$

## V. SOLUTION STRATEGY

The constraints of the optimization are non-linear though the objective function is linear. This section details the dynamic programming optimization used to solve the formulated problem.

### A. Dynamic Programming Optimization

Dynamic programming (DP) is an analytical optimization technique. The application of DP [19] to optimal microgrid architectures is highly prevalent because of the analytical solution it provides which might be very beneficial in planning purposes. The optimization problem is decomposed into stages and decisions are made to transit from one stage to the next. The DP decisions, states, stages and the optimization procedure are detailed in this section.

*DP decisions:* Decisions are the different combinations of unit additions which arise from an existing state of a current stage. It might happen that different decisions make different paths and arrive at the same configuration.

*DP state:* A state of the DP is a deployment configuration which arises by making a DP decision. Each state is associated with a reliability index and a system cost. From an existing state, all possible unit additions are considered. So the number of states to be stored in the memory increases as DP proceeds to the optimal solution.

*DP stage:* A DP stage is characterized by the total number of units added from the base case. All the states with equal number of unit links added which form different combinations constitute a stage. In a DP stage different states might correspond to same reliability index. It is not necessary however, to store the previous stages as we are interested in optimal solution, but not the path to the optimal solution.

*Identification of feasible solution:* The DP is solved in phases. Phase I starts building new stages and evaluating different decisions till the reliability of at least one solution in the current stage reaches the stipulated reliability criterion. Then the phase I ends and we have one initial feasible solution which forms the reference for phase II.

*Identification of optimal solution:* In phase II all the states which have cost greater than the reference state are eliminated. The remaining states are used to build subsequent stages. Whenever a decision ends up reaching a state which has the system cost greater than the reference cost, that trajectory ends. Whenever we encounter a state that satisfies the all the optimization constraints and has a cost lower than the reference state, that state is taken as the reference state. Phase II ends when all the trajectories have ended up with a higher cost than the reference cost.

If there are multiple solutions with same cost and different indices of reliability, the one with highest reliability is chosen as optimal solution. However the other solutions can be used as the alternate system plans.

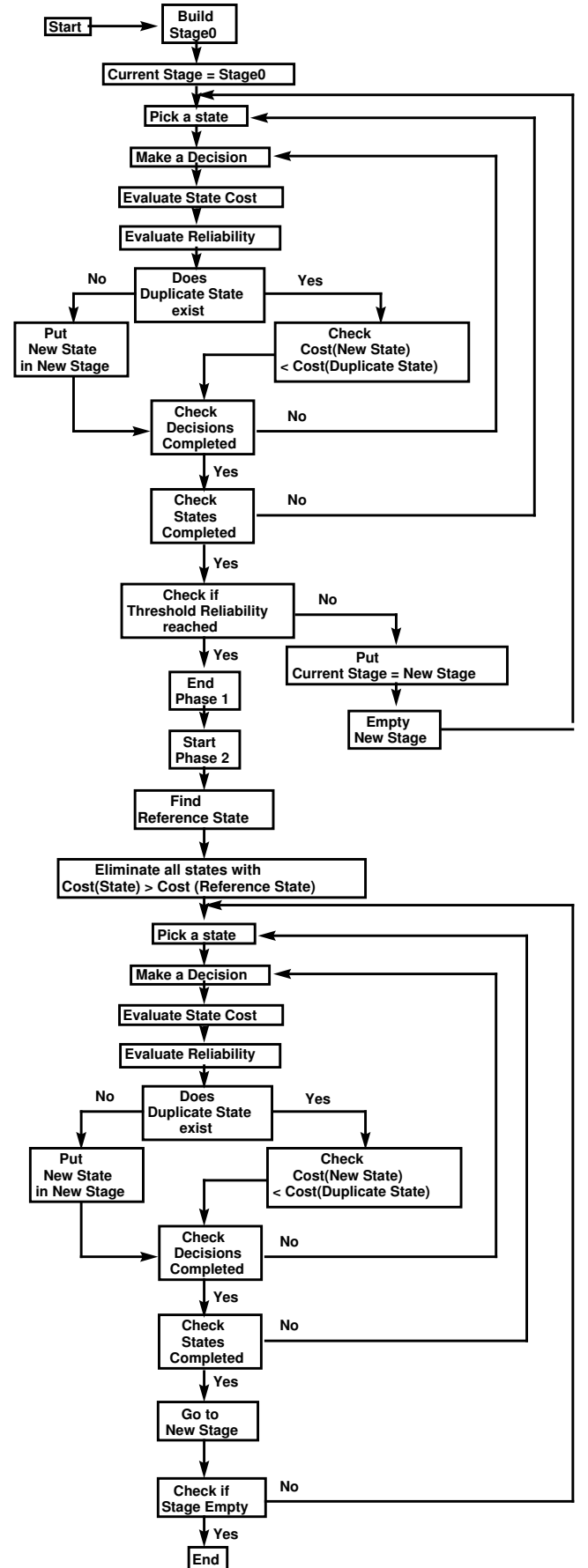


Fig. 1. Dynamic programming algorithm.

## VI. CASE STUDY & RESULTS

### A. System Description

The optimization strategy was applied on a 6 bus test system [21]. A load growth of 150% was considered and the deployment strategy was explored with no assistance from the grid. Nodes 2, 3, 4 and 6 are load buses with a total electrical demand of 21 MW. Also the load is separated into electrical and heating loads.

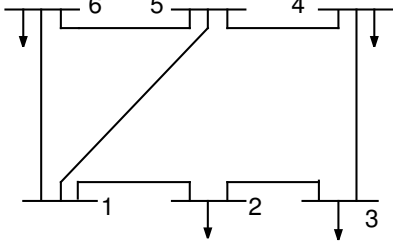


Fig. 2. Six bus test system.

TABLE I. LINE DATA

| From | To | Z (p.u)             | Susceptance (p.u) |
|------|----|---------------------|-------------------|
| 1    | 2  | $0.2238 + j 0.5090$ | 1.646             |
| 2    | 3  | $0.2238 + j 0.5090$ | 1.646             |
| 3    | 4  | $0.2238 + j 0.5090$ | 1.646             |
| 4    | 5  | $0.2238 + j 0.5090$ | 1.646             |
| 5    | 6  | $0.2238 + j 0.5090$ | 1.646             |
| 1    | 6  | $0.2276 + j 0.2961$ | 2.123             |
| 1    | 5  | $0.2603 + j 0.7382$ | 1.205             |

TABLE II. LOAD DATA

| Bus | Electrical Load (MW) | Heat Load ( $\times 10^6$ BTU/hr.) |
|-----|----------------------|------------------------------------|
| 1   | 0                    | 0                                  |
| 2   | 4                    | 6.824                              |
| 3   | 7.5                  | 10.236                             |
| 4   | 5.5                  | 6.824                              |
| 5   | 0                    | 0                                  |
| 6   | 5                    | 8.53                               |

The deployment costs of the DERs at each of the nodes is tabulated below.

TABLE III. DEPLOYMENT COST OF UNIT DER (IN \$ MILLION)

| Node | 1    | 2     | 3     | 4      | 5     | 6     |
|------|------|-------|-------|--------|-------|-------|
| MT   | 0.08 | 0.07  | 0.085 | 0.0825 | 0.075 | 0.082 |
| PV   | 0.46 | 0.45  | 0.465 | 0.462  | 0.452 | 0.462 |
| BS   | 0.16 | 0.158 | 0.165 | 0.162  | 0.159 | 0.161 |

The load profile is taken from the hourly load data on a typical day from the IEEE RTS79 [22]. For planning purposes the day with the yearly peak load was chosen.

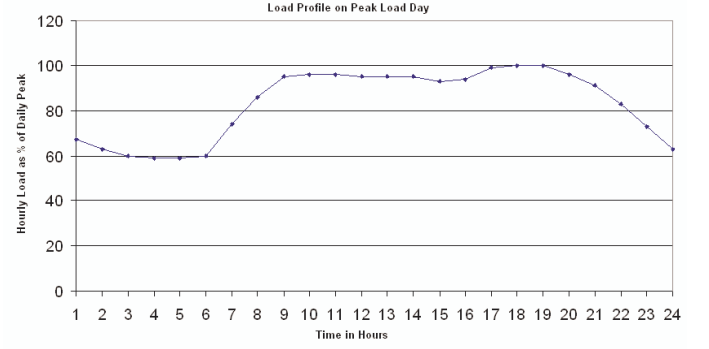


Fig. 3. Hourly load profile on the yearly peak day.

The variable capacity output of the PV is derived from the typical chronological data. Though the capacity builds up from morning to the afternoon, it is considered almost constant for the purpose of demonstration. The fuel costs are assumed a flat rate of \$100/MWH.

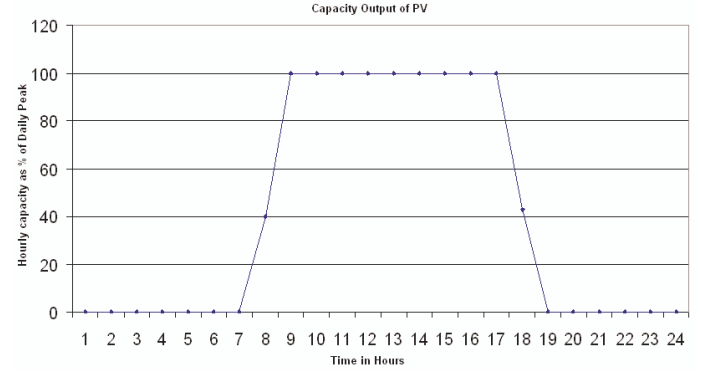


Fig. 4. PV hourly capacity curve on a typical sunny day.

### B. Results

The results obtained by applying the optimization strategy are tabulated below. A unit of MT is assumed to have a capacity of 0.1 MW electrical and  $0.1706 \times 10^6$  BTU/hr heat. A unit of PV has a peak capacity of 0.1 MW. A unit of battery has a energy capacity of 0.1 MWH.

TABLE IV. OPTIMAL SOLUTION FROM DP

| Node | MT | PV | BS |
|------|----|----|----|
| 1    | 0  | 18 | 0  |
| 2    | 71 | 68 | 64 |
| 3    | 52 | 19 | 70 |
| 4    | 22 | 26 | 54 |
| 5    | 0  | 36 | 0  |
| 6    | 60 | 16 | 38 |

The results show that more MT is placed near the load points by which most of its CHP could be utilized. But PV is more placed at those nodes where the deployment cost of PV is less, subject to transmission capacity constraints.

## VII. CONCLUSION

This paper presented a method based on dynamic programming to deploy DER in a manner that optimizes size, location and mix of resource types, subject to a stipulated reliability criterion. The economic benefits of deploying DERs were better exploited by considering the CHP mode. At the same time as DERs become more commercial, utilities need to estimate the heat loads of various consumers to better use the benefits of CHP.

The energy index of reliability computed can account for not only the transmission limitations of the microgrid, but also the time varying loads and generation capacities.

The 'big picture' in the context of cost optimal microgrids is to develop a comprehensive system which will be robust enough to sustain the future load growths with minimal system upgrade. In this direction work is in progress to unify the deployment and optimal topology strategies. Progress of the work will be reported in due course.

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