Switch Location Identification for Integrating a Distant Photovoltaic Array Into a Microgrid

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ABSTRACT Many Electric Power Systems (EPS) already include geographically dispersed photovoltaic (PV) systems. These PV systems may not be co-located with highest-priority loads and, thus, easily integrated into a microgrid; rather PV systems and priority loads may be far away from one another. Furthermore, because of the existing EPS configuration, non-critical loads between the distant PV and critical load(s) cannot be selectively disconnected. To achieve this, the proposed approach finds ideal switch locations by first defining the path between the critical load and a large PV system, then identifies all potential new switch locations along this path, and finally discovers switch locations for a particular budget by finding the ones that produce the lowest Loss of Load Probability (LOLP), which is when load exceeds generation. Discovery of the switches with the lowest LOLP involves a Particle Swarm Optimization (PSO) implementation. The objective of the PSO is to minimize the microgrid's LOLP. The approach assumes dynamic microgrid operations, where both the critical and non-critical loads are powered during the day and only the critical load at night. To evaluate the approach, this paper includes a case study that uses the topology and Advanced Metering Infrastructure (AMI) data from an actual EPS. For this example, the assessment found new switch locations that reduced the LOLP by up to 50% for two distant PV location scenarios.

INDEX TERMS photovoltaic, microgrid, switch placement, loss of load probability, optimization

I. INTRODUCTION

DISTRIBUTED energy resources (DERs), like photovoltaic (PV) systems, are a popular addition to electric power systems (EPS). Most often, roof-top PV system designs consider the offset of local energy consumption, economic incentives, and environmental impacts such as reducing dependence on fossil fuel generation. Unlike large “utility-scale” coal, nuclear, or hydroelectric plants, distributed PV systems are often situated close to the points of consumption. Their proximity to the load allows them to supply power to loads in a microgrid during an outage [1].

Larger distributed PV (dPV) plants, that are within the 500 kW to 10 MW explored in past hosting capacity work [2], are rarely sited in a way that considers resilience benefits for critical loads. Thus, incorporating these existing, distributed, community-sized PV resources into a microgrid may present integration challenges.

To understand the challenge and identify design considerations associated with the integration of distant PV into a microgrid, this paper proposes a spatial-temporal planning analysis methodology for a dynamic system that expands and contracts with the availability of generation resources. This approach identifies new switch locations between the critical load and the distant PV using the Particle Swarm Optimization (PSO) algorithm. The PSO algorithm finds the solution for a fixed investment cost that minimizes the critical load’s Loss of Load Probability (LOLP). This approach is helpful, because a utility may only have a budget that allows for three new switches to be installed and this analysis will identify the switch locations that maximize the critical load(s) days of uptime during electric grid outages. This is done by identifying disconnection points that will improve the LOLP...
metric, which quantifies the availability of generation and stored power to support the critical load.

Inclusion of a distant PV system requires the administration of dynamic microgrid boundaries. During the day the system expands beyond the critical load to include the distant PV system and non-critical loads. Then, at night the system shrinks to only power the critical load(s). A full understanding of the system’s ability to reconfigure and turn into a microgrid supplied exclusively by PV and batteries requires various types and levels of evaluation. Past research focuses on some technical aspects required to manage a stable dynamic microgrid [3], such as load balancing [4], dynamic analysis [5], and PV generation smoothing [6].

Unfortunately, these and other detailed analysis, modeling, and design activities require significant monetary and time investments. So, before major investments are made, the methodology presented here provides a utility with an understanding of the system’s capabilities. The proposed process does not include simulations that ensure stable electrical performance. A simulation of this kind would be performed if this assessment discovers a reasonable opportunity.

Creating and operating a dynamic microgrid inside an existing distribution system is possible and has been described in past work. Research efforts showed that EPSs with DERs and restoration capabilities can supply power to critical load(s) during a grid outage [7], [8]. Typically, these microgrids use fossil-fuel-fired generators, but studies [9], [10] and actual microgrid installations [11] now include PV as a major generation source. In most cases, the PV resources are behind the critical load’s meter or, if not behind-the-meter, the system is within the boundaries of the protection switches. But significant penetrations of PV dispersed throughout the EPS and advanced communications and controls present opportunities for integrating PV systems far from the center of the microgrid.

II. BACKGROUND

Advanced control strategies allow for the reconfiguration of network grids throughout the day to power both critical and non-critical loads [12], [13]. Some solutions leverage graph theory-based approaches to determine the switch configuration necessary to support critical loads during a contingency event [14]. Also, approaches like the spanning-tree algorithm can define restoration actions for a self-healing microgrid [15], [16]. One relevant paper proposed an optimization approach that discovers a cost-effective reconfiguration study [17], but does not attempt to discover specific switch locations that could improve microgrid operations. Another performance related study examined the synchronization of dynamic boundary microgrid with multiple islands [18]. However, pre-planning is needed to determine the distribution networks capabilities, which depend on load and generation amounts and their locations.

Past literature does address the placement of protection switches but does not consider locations useful for this application. Instead, past work focuses on the optimal placement of switches to improve system reliability under normal operating conditions, when the main grid is providing power [19]–[21]. One study considered switch locations for resilience to maintain proper power flows while the main grid’s power is still available [22]. Other work examined the placement of switches that allow for reconfiguration scheduling during a contingency event to avoid catastrophic outages [23], [24].

Published work examines various aspects of microgrid planning, and most focus on generation, storage, and the loads. For instance, one review paper discussed microgrid planning past work and listed such things as PSO algorithm for energy storage sizing, impact of fuel prices on planning, and many other aspects, but did not discuss switch location planning [25]. Another paper presents an approach for microgrid planning with uncertainty but does not evaluate boundary locations [26]. The authors could not find past work that focused on dynamic boundary planning for microgrids that involved the placement of new switch locations.

Work that is related to this analysis examines switches for microgrid operations. For example, one research paper evaluated the use of existing switches to define the size of the microgrid [27]. Or the optimal placement of switches within a microgrid [28]. However, to the best of the authors’ knowledge, none address the potential application where a microgrid attempts to integrate a distant PV system. The unique microgrid, in this case, can expand during the day to receive power from a distant PV plant to power both critical and non-critical loads. Then at night, the microgrid contracts to only support the critical load with the local battery storage and Grid Forming (GFM) inverter.

This paper expands on past work and provides the following unique contributions:

1) An assessment that identifies the optimal noncritical loads to disconnect so that the microgrid’s LOLP is minimized.

2) A planning assessment to identify the potential operations of a dynamic microgrid that expands to include some noncritical loads during the day and contracts at night, and during other low PV generation times, to only include the critical load.

III. DEMONSTRATION SYSTEM & PERFORMANCE W/OUT DISTANT PHOTOVOLTAIC SYSTEM

To effectively examine the proposed approach, this paper uses an actual EPS topology and load data. The assessment created theoretical dPV locations to test the potential integration of distant PV systems into a microgrid. The microgrid was assumed to support a single critical medical facility and included behind the meter PV, battery storage, and a GFM inverter.

A. ELECTRIC POWER SYSTEM

The demonstration EPS, shown in Fig. 1, includes 12 controllable switches, depicted by black triangles, that manage connections on three-phase lines. This 12.47 kV system has
a maximum length of 6.2 km to the furthest point from the substation. It supports 848 loads amounting to about 3.9 MVA (or 3.5 MW). Each load is monitored using AMI sensors that collect power data at 15-minute intervals. The critical load, discussed in Sec. III-B, includes a behind-the-meter PV and battery system. It also has a GFM inverter that provides the voltage source in off-grid mode and can operate in grid following mode when the grid is available.

This work assumes the desired microgrid days of autonomy to be three. Various organizations or entities have different thresholds or goals. For instances, the U.S. Army seeks to have 14 days of autonomy at their installations [35]. Civilian microgrids have less ambitious goals, such as two [36] or three days of autonomy [10].

To avoid complications, a PV and battery plant of sufficient size to power the critical load for three days of off-grid autonomy would be co-located. However, an appropriately sized PV and storage system may not be feasible at the critical load’s site based on cost and/or space restrictions. For example, the small medical facility, used in this evaluation test, has an 80 kW PV and 1,000 kWh (4,167 Ah) battery system capable of supplying 500 kW. The PV and battery of this size do not fully support the load reliably for longer than a 24-hour period.

The behind-the-meter PV system was simulated using the PVWatts [37] model in the Python PVLIB toolbox [38]. The simulations included a full year of operations using actual measurements from an irradiance sensor located near the critical load. The modeling effort accounts for the different azimuth angles of the PV subarrays (e.g., 200°, 230°) and the tilt angle (32°). The PV output results were combined with the load to estimate battery storage usage while in microgrid mode.

The actual building’s load, simulated PV, and battery usage over a year shows that the estimated battery state of charge (SOC) will completely deplete well before the end of a three-day period. For this site, the battery size matches the facility’s average daily energy usage (i.e., 1,019 kWh). Under these parameters, the time until the battery could no longer support the load varied between 17 to 42 hours depending on solar availability and the critical services electrical demands, as depicted in Fig. 2.

C. DISTANT PHOTOVOLTAIC ARRAY

To test the proposed methodology, the assessment assumed that the distribution system has an existing PV array far from the critical load. The assessment considered two scenarios. In one case, the PV system was placed at the location labeled PV System A and marked by an orange diamond in Fig. 1. The second scenario was a PV system located at location “PV System B”. In either case, the PV was assumed to have a 3 MW capacity. The fixed tilt system was modeled using

![FIGURE 1. This map shows the electric power systems topology and connected loads. It also highlights the location of the critical load (with its co-located resources) and two distant PV locations (at A and B).](image)

![FIGURE 2. The battery state of charge (SOC) never reached the full 3 days (72 hours) using the 80 kW PV and 1000 kWh battery. In the worst case, the SOC was depleted completely by hour 17. Under ideal solar generation conditions, the battery lasted until hour 42.](image)

![FIGURE 3. The distant PV system, at locations A or B, resembled a reasonable implementation where a significant portion of the load was offset but little to no reverse back-flow occurred at the substation.](image)
PVWatts and assumed to face due south at a tilt angle of 32°. An example output of the PV production is shown in Fig. 3 from August 19th to the 24th. The plot also shows the total EPS demand over the same period, and the PV makes up a significant portion of the daytime load.

IV. METHODS AND PROCEDURES

A distant PV system, already operational on the same distribution EPS, can provide a cost-effective generation source for an extendable microgrid. This is achieved through the control of smart switches along a path between the distant PV array and the critical load. Management using the existing electrical infrastructure may not result in a desirable balance between load and generation. Therefore, this planning assessment considers the system topology, existing switches, and load and generation over a single year to identify additional switch locations that improve the availability of generation and thus reduce the LOLP for the critical load.

A. INCLUSION OF DISTANT PV ASSESSMENT

This planning methodology intends to assess the microgrid’s ability to be dynamic and extend its boundaries to include distant dPVs that enable more off-grid autonomy for a critical service. The basic approach, depicted in Fig. 4, begins by processing three inputs: (1) grid topology information, (2) distant PV production and location, and (3) load, generation, and storage data. These inputs provide necessary data to define the existing switch zones and the shortest electrical path between the distant PV system and the critical load, which is necessary for identifying new switch location opportunities. Then, an optimization analysis, with an objective to minimize the LOLP, discovered the location for new switch locations.

1) Load & Generation Data Inputs

The single year of AMI and simulation data was separated into 120 three-day periods. This collection of three-day periods represented the different conditions for which occur during the different seasons of the year. Then, the optimization, described in Sec. IV-A2 below, iterated through the 120 periods to understand microgrid performance and discover the best new switch locations. Assessing these three-day periods throughout a full year found locations that will serve the system best at any time during the year.

2) Additional Switch Identification Approach

All the potential new switch locations provide inputs into an optimization algorithm. A PSO algorithm, based on the original PSO implementation [29] in the PySwarm toolkit in Python [30], was used. PSO was used in the past to identify protection switch locations [31]. In this case, this application is different because the PSO algorithm iterates through possible operating scenarios and consider the inclusion or exclusion of each potential section that can be disconnected to find the switch locations that minimize the LOLP. Exclusion of a switch in the optimization analysis meant that the section was removed, and the loads were not included in the microgrid’s daytime operations. Inclusion meant that section was part of the microgrid and the noncritical loads were served. The algorithm performed the optimization using a position-velocity update method. The position is defined by Equation 1:

\[ x_i(t + 1) = x_i(t) + v_i(t + 1) \]  

where \( x \) is the position, \( t \) is the current timestep, \( i \) is each particle, and the velocity update is described in Equation 2:

\[ v_i(t + 1) = w \cdot v_i(t) + c_1 r_1(t) [y_i(t) - x_i(t)] + c_2 r_2(t) [\hat{y}_i(t) - x_i(t)] \]  

where \( r_{1,2} \) are random values between 0 and 1, \( y \) is the best personal position of an individual in the swarm, and \( \hat{y} \) is the best position found by the swarm. For this work, the \( c_1 \) (cognitive parameter), \( c_2 \) (social parameter) and \( w \) (inertia)
were set to 0.5, 0.5, and 0.2 respectively. The acceleration parameters \(c_1, c_2\) were the same to create a balance between what \(32\) describes as nostalgia \(c_1\) and envy \(c_2\). This approach avoids excessive wandering or the premature rushing to an optima. And \(w\) matched the criteria defined in \(32\) based on the \(c_1\) and \(c_2\) set values.

The PSO algorithm is unique, because it does not depend on the gradient of the objective function to discover an optimal solution. Instead of using a gradient descent to find a global minimum, the algorithm moves based on \(y\) and \(\hat{y}\). The algorithm also, can converge to an optimal solution in a timely manner because the multiple particles were updated in parallel and it each iteration the best position, \(\hat{y}\), was identified only once.

The optimization iterates through load and PV data at one-hour intervals and considers battery charge/discharge limits (500 kW), PV availability depended on the amount of irradiance, and the microgrid’s load. These limits constrained the electrical system to only include the distant PV array during the day when generation exceeded the microgrid load.

The general operations of the dynamic microgrid are represented in Fig. 5 with the time series plot over a two-day period. The dotted light grey line, in Fig. 5, shows the overall feeder load for reference. The feeder load is reduced to only a critical load at night and certain sections of the feeder during the day, as depicted by the green solid line in Fig. 5.

During the day, when there is excess PV, the critical load’s battery is charged, and the remaining PV power is curtailed. The critical load, shown by the blue line in secondary y-axis, always remains powered using the on-site battery during the night and the distant PV system during the day.

This energy analysis provides a preliminary understanding of the basic capabilities of the system and potential upgrade options to improve microgrid autonomy lengths. Note that no power flow solutions were performed, but that due to the radial nature of the system we know that no lines will be overloaded otherwise the existing PV and critical customer could not be served during normal operations. After this initial assessment, more detailed simulations would have to be performed to investigate voltage, protection, and stability of the proposed system.

The optimization process minimized the LOLP probability for the microgrid. The LOLP calculation was used in past work to determine the optimum size for PV systems \(33\) and to assess the reliability of a microgrid power system \(34\). The calculation compares the available power generation with demand over time using Equation 3:

\[
LOLP = \frac{\sum_{j=1}^{N} u(j)}{N} \cdot 100
\]  

where \(N\) is the total number of hours and \(u\) is a unit-step function defined by Equation 4:

\[
u(j) = \begin{cases} 
1, & \text{if } P_{PV}(j) + P_{B} \leq P_D(j) \\
0, & \text{if } P_{PV}(j) + P_{B} > P_D(j) 
\end{cases}
\]  

where \(P_{PV}, P_D,\) and \(P_B\) are the power generation, demand, and available battery storage for the microgrid respectively.

Therefore, the optimization objective function, that minimizes the LOLP, is as follows:

\[
\min_{u, N} \frac{\sum_{j=1}^{N} u(j)}{N} \cdot 100 
\]

\[\text{s.t. } P_B(j) \leq |500|, \]
\[P_{PV}(j) = P_{PV_1}(j), P_{PV_2}(j) + 50 < P_{D_T}(j), \]
\[P_D(j) = P_{D_1}(j), P_{PV_2}(j) + 50 < P_{D_T}(j), \]
\[P_{PV}(j) = P_{PV_2}(j), P_{PV_2}(j) \geq P_{D_T}(j), \]
\[P_D(j) = P_{D_T}(j), P_{PV_2}(j) \geq P_D(j) \]

\(P_{PV_1}\) represents power generation from the local \((P_{PV_1})\) plus the distant \((P_{PV_2})\) PV systems. \(P_{D_T}\) was the local demand \((P_{D_1})\) plus the extended microgrid load demand \((P_{D_T})\).

3) Survivability Assessment

After finding the new switch locations, a secondary analysis identifies the outage survival probability for each microgrid scenario. To calculate the survival probability at each hour of
a three-day period throughout the year the following equation was used:

\[ P(A)_h = \frac{n(A)}{n(A) + n(B)} \times 100\% \]  

(5)

where A is an event where sufficient PV or battery energy is available to supply the load, B represents an opposite event where there is not enough energy to support the load, \( P(A)_h \) is the probability of an event A at each hour of the three-day period (between 1 and 72 hours), \( n(A) \) is the number of A outcomes, and \( n(B) \) is the number of B outcomes.

V. RESULTS

The results section reviews three key areas that highlight the new planning assessment’s outputs for the test EPS, critical load, and large-scale PV array.

A. SWITCH LOCATION OPTIONS

The identification of potential switch locations was conducted on the demonstration EPS for two large-scale PV array locations (i.e., PV System A and PV System B shown in Fig. 1). The switch zone locations for the two scenarios are depicted in Fig. 6 and Fig. 7. These figures display the EPS in a graphical format by aggregating the switch zones into single circles with numerical labels. The numbering begins at zero, which is at the EPS substation. The connecting edges between the zones have various colors and sizes to represent different connection types. The gray/thin edges describe where existing EPS switches are located. For example, Fig. 6 shows that zones 0, 1, 2, and 3 are connected by existing switches. The thicker red lines connecting the zones represent potential new switch locations. Finally, the thick black lines define the shortest path between the PV array and the critical load’s switch zone.

Fig. 6 shows the existing and potential switch zones for the distant PV located at “PV System A”. Zone number 17 included the distant PV array and was connected to the critical load, in zone 38, through zones 7, 5, and 35. For this scenario, there were 66 laterals connected to the path between the PV and critical load that could be segregated with a new switch to improve microgrid days of autonomy.

In the case where the distant PV was located at “PV System B”, Fig. 7 shows the path between zones 3 and 24. The PV array was in zone 3 and the critical load was inside 24. There was a total of 43 laterals without switches connected to the 3, 5, 6, 21, and 24 zones that were directly within the shortest path. All these laterals, indicated by the red lines in the two figures, were considered in the analysis methodology.

B. OPTIMAL SWITCH LOCATIONS

The optimization discovered the 1, 3, and 5 new switch locations that minimized the LOLP for a microgrid operating over various three-day periods throughout an entire year. The results from this optimization process are summarized in Table 1. The baseline case, where no new switches were added, demonstrated a LOLP of 10.4% and 6.2% for PV array locations A and B, respectively. Location A had a higher LOLP value because the path included more loads.

The images in Table 1 depict the potential size of the microgrid that connects the critical load with the distant PV system, and other loads. In the case where no switches were added, the red area indicates the size of the microgrid and the light grey shows the sections that currently can be disconnected with the existing switches. For the scenarios where 1, 3 and 5 switches were added, the new switching capabilities are indicated by the dark grey sections. These dark grey areas are lateral sections connected to switches that could best reduce the LOLP.

The optimization found new switch locations for scenario A that reduced the LOLP from 10.4% to just above 5%. If only one new switch location was considered, the removal of zone 21 would produce the best LOLP (7.6%). The microgrid would then serve 318 loads (1.7 MW) during the day. The LOLP was reduced further to 6.3% if only 167 loads (during the day) and the critical load (all day) were served with the
addition of three new switches disconnecting zones 21, 15, and 29. The final assessment considered the implementation of five new switches, which reduced the LOLP to 5.1% for 95 loads and the critical load. To achieve the 5.1% LOLP, zones 21, 15, 19, and 39 would need to be disconnected from the microgrid.

In the case where the distant PV array was located at position B, the LOLP ranged from around 4% to 6% as shown
in Table 1. An additional switch would best be utilized if it disconnected zone 15 and only served 145 loads during the daylight hours. When considering three new switch locations, the optimization found that the removal of zones 15, 25, and 4 would result in an LOLP equal to 5.4% when supporting 79 loads. The best five zones, identified by the optimization for this PV location scenario, were 15, 25, 4, 14, and 32. Disconnecting these five zones reduced the LOLP to 4.4% for only 39 loads.

C. MICROGRID SURVIVABILITY

The removal of loads using switches improved the microgrid’s ability to operate over a three-day period. If the critical load was to operate on its own, using its own local PV and battery, the microgrid will likely not last past 30 hours. Fig. 8 shows that the outage survival probability for the critical load powered only by the local 80 kW PV and battery storage has less than a 5% chance of reaching 72 hours (or three days).

The outage survival probability rose considerably with the inclusion of the distant PV array and shedding of non-critical load using only the existing and new switches. This result indicates a significant gain (from 5% to 74%) in microgrid operations with the inclusion of the distant PV array and shedding of non-critical load using only the existing and new switches.

The inclusion of the PV array at location B depended less on additional switches to raise the survival probability. In this case, the minimum survival probability was estimated to be 84% without any new switches, as shown in Fig. 8. The additional new switches had very little impact on the results; the survival probability rose slightly to 85% when one, three, and five switches were added.

D. COST COMPARISON

The addition of 1, 3, and 5 new switches, for the two PV location scenarios, improved the resilience of the critical load at a lower cost than the addition of local PV generation and storage. This result assumes that the existing, distant PV array can be integrated at no cost for resilience - since the system, like many community solar installations, was originally installed based on other financial considerations and not for resilience.

Fig. 9 compares the extendable microgrid options with scenarios that increase the amount of PV and storage at the critical load. For this assessment, the carport PV at the critical load was assumed to cost $3.72 per watt [39] and the battery was $130 per kWh [40]. Adding more PV at the critical load...
had little impact on the estimated LOLP percentage, and only reached just above a LOLP of 20% after spending $446,000. Money spent on more battery storage would improve the LOLP at a higher rate than the case where only PV was added. More electrical storage caused the LOLP to drop below 10% after spending just under $200,000 and below 1% after spending around $325,000.

To make the extendable microgrid options work, it was assumed to only require additional switches to connect an existing PV array to the critical load’s GFM inverter. The cost to add a single switch was assumed to be $50,000. Using the existing switches, implemented originally for system protection, resulted in more LOLP percentages at or below 10%. Investing $50,000 and $150,000, to install one and three switches respectively, reduced the LOLP slightly, but in each case were lower than the addition of PV and battery storage. The addition of five new switches resulted in an upfront cost of $250,000, which was slightly higher than the cost to add more storage to achieve a lower LOLP percentage.

VI. DISCUSSION

This analysis is only investigating N-1 scenarios of losing power from the bulk system during a resilience event. It does not consider multiple outages where the bulk system is out and then there is an additional failure inside the microgrids that would have to be isolated by the microgrid protection system. Under those extreme scenarios, the survivability results may change because the extendable microgrid to the distant PV might not be able to connect to the critical load due to an additional outage.

The initial hypothesis anticipated that the daylight and nighttime profiles would influence the results and therefore the overall energy could not be useful for identifying the best switch zones to form a microgrid with the lowest LOLP. The assessment assumed that the microgrid only extended out to include the distant PV array during the day, and at night it only included the critical load. The non-critical loads were only powered during the day and their load profiles varied based on the available historical AMI data. Fig. 10 shows evidence that contradicts this hypothesis. It turns out that the switch zones’ overall energy for the year matched with the LOLP optimization results.

In the one new switch scenario for the large PV system located at A, the largest switch zone energy was number 21, as shown in Fig. 10, which also produced the lowest LOLP in the optimization. The three and five new switch scenarios’ annual energy also matched with the optimization results. The three-switch case showed that 21, 15, and 29 had the highest total energy. The top five energy-consuming zones (21, 15, 29, 19, and 39) also matched with the LOLP results.

The comparison of the annual energy confirms the optimization results. It also shows that it could potentially be used instead. However, there may be circumstances where the total energy of the switch zone is substantially larger during the daytime hours compared to the night.

Also, there could be situations where the switch zone’s total energy is nearly equal and may not offer a clear choice. For example, for both switch zones 19 and 39, total annual energy equals around 30,000 MWh. The optimization found that with a 3 MW PV system, the number of hours without power over the entire year was equal (i.e., 807 hours) if 19 or 39 were removed. However, if the PV system was 1 MW and zone 39 was removed it would result in 80 more hours with power compared to if 19 was removed.

VII. CONCLUSIONS

At different budget levels (i.e., set number of switches to install), the proposed methodology identified locations that
minimized the critical load’s autonomy duration by finding switches that minimize the LOLP. The expansion of the microgrid to include the distant PV system along with non-critical load shedding resulted in LOLP of less than 10%. The probability of survival rose from 5% to over 70% when using the existing switches. It improved even more (above 80% probability of survival for a three-day period) when one, three, and five switches are added to remove groups with considerable non-critical loads.

The analysis also compared the switch results with other possible upgrade options, such as increasing the size of PV or battery storage. The evaluation found that money is better spent on load management through the strategically placed switches identified using the proposed methodology.

Using this approach, a dynamic microgrid could potentially power many noncritical loads during the day because of the inclusion of the distant PV array. Then, at night, all of the noncritical loads will be disconnected and only the critical load will be powered. This offers communities the opportunity to power critical loads continuously and provide some power to noncritical loads when conditions allow for the expansion of the microgrid.

This approach successfully identified sections that consumed the most energy, as described in Sec. VI, using the PSO. Therefore, other optimization or analysis methods were not tested. However, this paper only tests the PSO approach on a single distribution EPS. Further studies are required to understand its ability to identify sections accordingly on different EPS. Other analysis and optimization techniques can also be explored in future work and compared with the PSO approach used here.

Future work is also necessary to understand operations in more detail. Additional studies should evaluate the method on other feeders to understand its repeatability. Follow-on studies can also include the sizing and operations of a GFM inverter to ensure stable microgrid operations with high penetrations of grid-following PV. Also, different effective methods for identifying locations and managing existing control devices (e.g., regulators, load tap changers, capacitors) to work with GFM inverters should be investigated. Finally, reconfiguration protection schemes are required to be updated to account for different topologies and power flows.

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