Design Flexibility for Uncertain Distributed Generation from Photovoltaics

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***Abstract*—Uncertainty in the future adoption patterns for distributed energy resources (DERs) introduces a challenge for electric distribution system planning. This paper explores the potential for flexibility in design–also known as real options–to identify design solutions that may never emerge when future DER patterns are treated as deterministic. A test case for storage system design with uncertain distributed generation for solar photovoltaics (DGPV) demonstrates this approach and is used to study sensitivities to a range of techno-economic assumptions.**

***Index Terms*—Distribution System Planning, Flexibility in Design, Real Options, Dynamic Programming**

I. Introduction

Increasing deployments of distributed energy resources (DERs)—including solar, storage, smart homes, and electric vehicles—can require modifications to electric distribution systems to maintain system voltage, reliability, power quality, or other operating constraints. Today most of these changes are reactionary—waiting until a problem is observed, or until the N^{th} DER interconnection request crosses a threshold and requires mitigation. This paper explores the opportunities to go beyond reactionary design to show the potential for forward-looking planning that identifies flexible design options with optional upgrade paths making it easier and cheaper to adapt, if needed, to uncertain future DERs.

Most past published efforts in distribution design optimization have focussed on distribution expansion, load growth management, and reconfiguration (e.g. [1]–[6]). Lindl, et al. [7] present a detailed discussion of the challenges of designing for high DER futures and propose the proactive integrated distribution planning (IDP) approach for accommodating high penetrations of DERs. IDP clearly articulates five steps for proactive planning, but does not dig deeply into stochastic decision making. Some past efforts in power systems have considered stochastic distribution design (e.g. [8]) but have not looked at the distribution planning problem for DER integration. Design under uncertainty, or real options approaches, have been successfully used for other problems to capture optimal, multi-period technical decisions in the face of uncertain future scenarios [9], [10]. Several studies consider distribution planning for DER futures [11]–[13] using deterministic and stochastic genetic algorithms for optimal sizing and location of DERs; however, they propose the DSO as a centralized planner and do not take into consideration the DSO's need to respond to customer adoption of DGPV. This paper combines these threads by demonstrating the potential of flexibility in design for distribution planning to provide improved designs for stochastic DER futures with an example involving storage and DGPV.

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II. Problem Formulation and Methodology

A. Motivating example

To motivate the opportunities for design flexibility with DERs, consider a feeder facing large, but uncertain, growth in distributed generation from solar photovoltaics (DGPV). Also, assume the transmission operator strictly limits reverse power flow from the feeder and imposes an energy penalty to the distribution system operator (DSO) for any backfeed. As a result, the DSO plans to proactively install a substation battery storage system.

The question for the DSO is how to size the storage system. For simplicity, assume there are only two storage size options under consideration: Small and Large. If DGPV adoption is high, then the utility will need the large storage system to prevent backfeeding. However, if DGPV adoption is low, the smaller, cheaper storage system will suffice. If the future DGPV adoption pattern was known, the DSO would pick the corresponding storage size; however, because of uncertainty, the DSO may either over-invest in storage–if DGPV adoption is lower than expected–or pay high backfeeding penalties–if DGPV is larger than expected[1].

For the sake of illustration, assume that the DSO has two planning periods. The DSO must first decide about the (initial) storage size before the initial uncertain adoption of DGPV occurs. During the next planning period, it can choose to modify the storage size before a final period of uncertain DGPV

[1]assuming a regulatory environment or lack of communication infrastructure prevents curtailing DGPV

adoption. This sets up a classic, two-stage decision making under uncertainty problem, where the DSO seeks to minimize the expected value across all scenarios. In our example, consider that the DSO has three initial choices:

1. A large (both power and energy) battery storage system,
2. A small battery storage system, and
3. A flexible design option[2], where the DSO initially invests in sufficient infrastructure (e.g. transformer, inverter) for a large power-rated storage system, but only installs a few batteries, with small energy capacity. Then if DGPV growth is large the DSO can choose to install additional batteries to produce the same large system rating as in choice 1. The choice to attain this flexibility typically results in a higher initial cost, but the DSO's ability to adapt to change can reduce total expected operating costs under uncertainty.

This example can be represented graphically as a decision tree (Fig. 1). In this representation, squares represent decision nodes, circles represent uncertainty nodes, and triangles show terminal (post-final-decision) values.

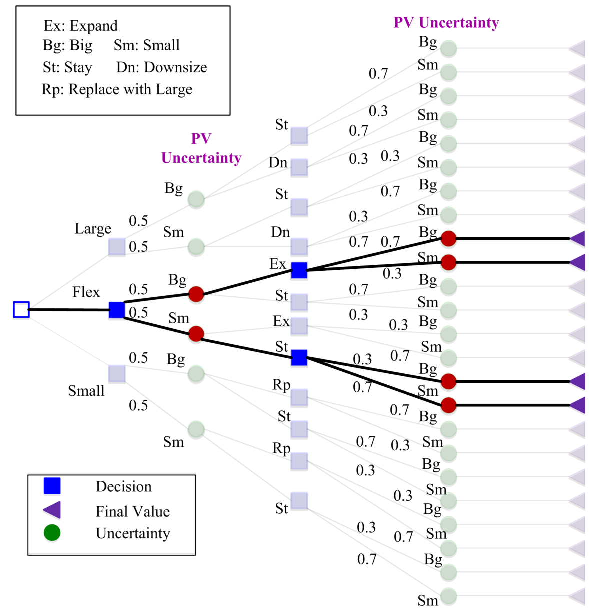


Fig. 1: Decision tree for storage sizing example with optimal path highlighted

B. Solution Methodology

The optimal first period decision can then be found working backwards:

1. Compute the operating cost for the terminal nodes
2. Compute the expected value for each uncertainty node
3. For each decision node, pick the decision with the lowest sum of decision cost plus expected future value
4. Repeat steps 2 & 3 until to find the optimal first decision.

C. Dynamic Programming Equivalent

This approach can be represented more rigorously as a dynamic program, which is formulated using a form of Bellman's equation [14], [15]:

$$\min_{\Pi} J_{\Pi}(x_0) = E\left\{ g_N(x_N) + \sum_{k=0}^{N-1} g_k(x_k, \mu_k(x_k), w_k) \right\}$$

where

- Each policy, Π consists of a sequence of decisions

$$\Pi = \{\mu_0(x_0), ..., \mu_{N-1}(x_{N-1})\}$$

  where μ_k maps states x_k into controls $u_k = \mu_k(x_k)$ such that the control constraint is satisfied, i.e., $\mu_k \in U_k(x_k)$.
- $J_{\Pi}(x_0)$ is the expected cost of policy Π starting as x_0,
- k is the stage index,
- x_k is the state of the system including existing storage power, existing storage capacity, and existing PV deployment pattern,
- u_k is the decision variables to be selected at stage k, which includes new storage capacity and new storage power rating,
- w_k is the uncertain parameters, i.e., PV growth,
- N is the number of stages,
- f_k is a function that describes the operating cost of the distribution system and in particular the mechanism by which the state is updated:

$$x_{k+1} = f_k(x_k, u_k, w_k), \quad k = 0, 1, ..., N-1$$

- $g_N(x_N)$ is a terminal operating cost incurred at the end of the planning process.

The objective of the planning problem is to minimize $J_{\Pi}(x_o)$ for a given x_0 over all Π while satisfying various constraints of the planning problem. This problem can be efficiently solved by using dynamic programming (DP) with backward induction, the steps of which are as follows:

- Step 1: Let $k = N$; simulate the distribution system operation by using OpenDSS [16] and obtain $g_k(x_k)$ for each terminal node in Fig. 1;
- Step 2: let $k = k - 1$; calculate decision cost, operating cost, plus the discounted expected future cost at each decision node; pick the lowest value as the cost to go and record the decision with the lowest value; Repeat this step until $k = 0$;
- Step 3: Obtain the optimal policy by forward looking into the recorded decisions across all uncertainty nodes.

[2]also known as a real option

III. CASE STUDY

A. Test Case

A modified IEEE 13 bus system is used to perform a case study to test hypothesis stated above. An additional bus was added between bus 632 and bus 670 to simulate the distributed load along line 632-670. As described in Section II-A, there exists an uncertainty in the DGPV adoption that occurs over multiple planning periods scenarios. Two decision points were chosen for this example and assumed to correspond to 2016 and 2020. After each decision, it is assumed that DGPV growth can be either low or high with in the second planning period correlated to the growth in the first time horizon. Various penetrations of PV were picked based on expected growth of PV and type of load at individual zones. The growth of PV at each zone is described in detail in Table I. Fig. 2 shows a comparison of the base PV penetration and a future "high" PV scenario.

Time synchronous load and PV time series are used for four representative days in the 2014—Jan 15th, April 15th, July 15th and Oct 15th. Solar data was taken from the National Solar Radiation Database (NSRDB) [17] for Santa Clara, CA. This solar irradiance information was fed into System Advisory Model [18] to calculate PV power output for the entire year. The historic load shape for Medium General Demand-Metered Service (A10 load profile) from PG&E [19] was used as the baseline and was scaled at each bus proportional to the load specified in the standard IEEE 13 bus system.

Storage costs are based on a combination of battery costs calculated from a logrithmic curve fit of Li-Ion batteries from [20], storage inverter costs from [21], and exponential extrapolation of transformer costs from [4]. The baseline discount rate (time value of money) was taken as 4%/year and the backfeeding penalty was assumed as \$0.27/kWh.

B. Simulation Approach

The test case was built and solved as a decision tree using a custom Microsoft Excel spreadsheet that managed multi-period optimal decisions, discrete uncertainty, discounted net present value, and cost assumptions. This approach enabled rapid exploration of the problem space including sensitivity analysis. Power system operations simulations were performed using OpenDSS Version 7.6.4 through the COM interface using an automated Python script. OpenDSS captures key electrical phenomena such as additional network losses from the storage and DGPV location patterns. A peak-shifting storage control algorithm was implemented in Python that reduces peak net demand periods to fill-in minimum net demand periods, subject to storage power constraints, energy capacity constraints and state-of-charge constraints. This control signal is provided as an input to the storage device in OpenDSS. With high solar deployment, this effectively minimizes feeder backfeeding. Using OpenDSS, the backfeeding of power at every hour is calculated for various scenarios. Fig. 3 shows example time series results from this algorithm in OpenDSS. It compares the feeder-head net demand for a DGPV penetration case with and without three types of storage systems. The scenario tree constructed in Excel is used to calculate the optimal decision at every period based on input costs and backfeeding in the various scenarios.

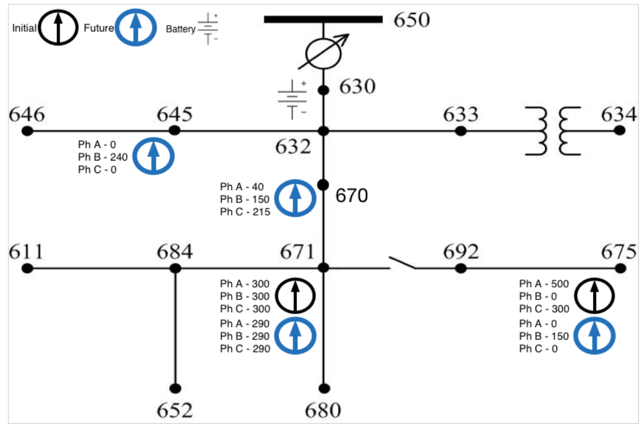


Fig. 2: Modified IEEE 13 Bus Single Line Diagram

C. Results and Discussion

1) The case for flexible design: As seen in Table IV, the optimal initial decision is the flexible storage design. The expected net present value (E(NPV)) of the flexible design in the face of uncertainty is \$32,441 lower than the next best option. As seen in Fig. 1 the choice to exercise, or not, the real option of expanding the storage depends on the outcome of the first period uncertainty. Specifically, if the adoption of DGPV is "big" then the optimal decision is to expand the storage unit; however, if DGPV growth is small, the flexible design allows for staying at a small size. Moreover, as also shown in Table IV, the flexible design noticeably reduces the range of possible cost outcomes within the uncertainty space. Compared to the next best E(NPV) option, the non-flexible small storage size, the flexible design reduces the worst case outcome by over \$230,000, while only hurting the best case scenario by \$117,000.

2) Sensitivity: When is design flexibility more important?: The value of flexibility in design depends on a large number of techno-economic factors. This section explores the sensitivity of the above results to a number of assumptions as summarized in Table III.

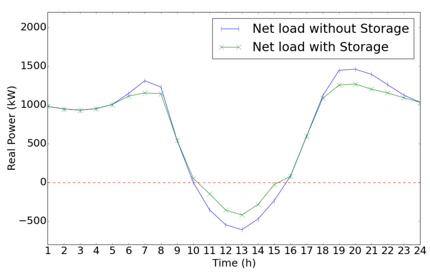
a) Storage Cost Trends - The baseline assumptions align with current projections for storage costs to decline rapidly. This actually makes it more difficult to justify the flexible design's partially oversized initial investments. If the costs dropped faster, investing small to start and replacing with future cheaper storage if needed would have a cheaper expected cost. In contrast, if storage costs were assumed constant (in real dollars) the E(NPV)

TABLE I: IEEE 13 bus system PV Penetration (kVA) in Various Scenarios

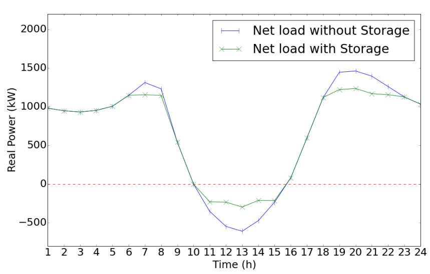
IEEE bus name	Initial	Small	Big	Small-Small	Small-Big	Big-Small	Big-Big
671.1	300	300	300	400	500	400	590
671.2	300	300	300	400	500	400	590
671.3	300	300	300	400	500	400	590
645.2	0	0	240	200	200	240	240
675.1	500	500	500	500	500	500	500
675.2	0	0	90	0	75	150	150
675.3	300	300	300	300	300	300	300
670.1	0	20	40	40	20	40	40
670.2	0	75	150	95	75	150	150
670.3	0	125	200	125	125	215	215
Total	1700	1920	2420	2460	2795	2795	3365
Capacity Penetration	76%	86%	109%	111%	126%	126%	151%

TABLE II: Input assumptions

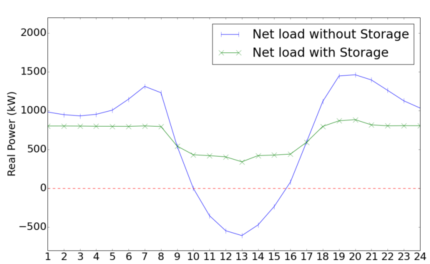
Year	Inverter $/KW	Transformer $/kW	Battery $/kWh
2016	$150	Power Law Curve Fit	$352
2020	$90	Same as P1	$250



(a) 5 hour 1000 kWh capacity BESS



(b) 1 hour 1000 kWh capacity BESS



(c) 5 hour 5000 kWh capacity BESS

Fig. 3: Results case with low growth of PV in period 1 and high growth of PV in period 2

advantage of the flexible design increases 60% to $51,790 (see Table III).

b) Modular Storage - The baseline assumes that if the initial decision is to build an inflexible small storage system, the option to expand storage to account for high DGPV growth would have to scrap this small system and build a new large one. If instead, the storage system had a modular design that allowed the inverter and battery capacity to be increased by 800kW and 4000kWh, respectively, the optimal first period decision would change to the small system and save $84,234 in E(NPV) terms. Effectively, such a modular design represents another type of flexibility in design, similar to the baseline "flexible" option.

c) DGPV growth correlation - As seen in Fig. 1, in the baseline early DGPV growth greatly increases the likelihood of further second period DGPV adoption. If instead, early high adoption made future growth less likely, the first period decision changes to the fixed small design. For example if the probability of "big" DGPV growth in P2 given "big" PV growth in P1 were only 47% (or lower), the initial small design would be $1,249 (or more) cheaper than the flexible design.

d) Discount rates - Lower discount rates, also favor the flexible design. Increasing the discount rate to 9% (or higher) switches the optimal initial decision to the small design, since future operations and decisions have less impact on current decisions.

e) Backfeed penalties - Similarly, high operations costs–in this case high backfeed penalties–also favor the flexible design. If backfeeding penalties were reduced to $0.19/kWh (or lower) the small option would be best.

IV. CONCLUSIONS

This paper demonstrates how in the face of uncertain adoption patterns of DERs, a flexible technical design for distribution system mitigation strategies, can reduce integration costs, tighten their possible range, and reduce the worst case. Here, the option of initially oversizing a storage system's power rating provided the lowest expected cost (net present value)

TABLE III: Sensitivity Analysis

Case	Storage Cost	P(big-if big)	P(sm-if-sm)	Disc Rate	Storage	P1 Decision	BackFeed	E(NPV) Sm-Flex
Baseline	Baseline	80%	80%	4%	Non-modular	Flex	$0.27	$32,441
Const. Storage Cost	Constant	80%	80%	4%	Non-modular	Flex	$0.27	$51,790
Modular Storage	Baseline	80%	80%	4%	Modular	Small	$0.27	-$84,234
Anti-causal DGPV	Baseline	47%	47%	4%	Non-modular	Small	$0.27	-$1,249
Higher Discount	Baseline	80%	80%	9%	Non-modular	Small	$0.27	-$5,976
Lower Penalty	Baseline	80%	80%	4%	Non-modular	Small	$0.19	-$12,534

TABLE IV: E(NPV) of decision costs

Decision	E(NPV)	Best Case	Worst Case
P1 Large	$(1,978,744)	$(1,758,961)	$(2,226,158)
P1 Flex	$(1,080,352)	$(550,961)	$(1,797,065)
P1 Small	$(1,112,793)	$(433,735)	$(2,036,200)

for mitigating backfeeding penalties in the face of uncertain DGPV adoption levels. In a later decision period, the flexible design enables easily choosing whether or not to expand the system. Flexibility in storage system design can offer real benefits for uncertain DER futures; however, the value of such flexibility is somewhat scenario specific. Design flexibility is more valuable in situations where future decisions and costs have high value today. This includes lower discount rates, technology prices that don't fall too fast (although even the current precipitous drop in storage prices is "slow" enough to find value), and large, long-lasting investments. Design flexibility is also favored when early indications of uncertain trends can help predict future patterns–such as when rapid early adoption of DERs foreshadows continued high deployments. These flexibility-encouraging characteristics are typical of many electric distribution system investments suggesting that flexibility in design methods–or more generally dynamic programming–may offer a promising approach for identifying robust integration strategies for uncertain DER futures.

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