Distribution level battery storage valuation framework

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Abstract

The growing demand for electricity in emerging markets and developing economies such as India is causing loading and congestion problems on distribution networks, particularly in urban locations. Electric utilities in these regions face unique constraints regarding raising capital required to upgrade their congested networks. Battery storage has emerged as a non-wire alternative to feeder-level upgrades. This article presents a valuation framework by optimally sizing and placing battery storage on the distribution network. We evaluate the value of storage using a real options analysis through a Markov Chain Monte Carlo to identify the least-cost network upgrade strategy, given demand growth uncertainty. When applied to urban distribution network feeders typical of those found in congested cities in India, the approach highlights the economic value of network investment deferrals by making use of battery storage. We find that storage costs below 261 USD/kWh justify investments in distribution level storage and storage as a non-wire alternative only makes sense on moderately loaded feeders where storage charging is still feasible without violating network thermal capacity limits.

Keywords: Battery storage, power distribution networks, investment
1. Introduction

The electrical grid is a complex system typically powered by a centralized generation with flows subject to non-linear physical laws. Generation is stepped up to a higher voltage level for transmission to large load centers, i.e., urban areas; it is then stepped down to the appropriate voltage for distribution to end-consumers, including residential, commercial, and industrial users. Investments in the electrical transmission and distribution network tend to be lumpy since they require large capital commitment initially, involve significant economies of scale, and the resulting assets have long lifetimes (20 to 40 years). Consequently, network planning is often employed to identify the investments needed to meet future demand reliably and cost-effectively, maximizing asset utilization. For reliable grid operations, network cable capacity must meet peak electricity demand while adhering to equipment operating constraints (e.g., line thermal limits). Substantial economies of scale and voltage step-up encourage investment in high-capacity lines and very long-term planning at the transmission level, but this is not always the case at the distribution level in emerging markets and developing economies (EMDE), where distribution companies usually are financially constrained, and networks are more congested. Here, we develop a flexible valuation framework to analyze the optimal sizing and placement of storage and its economic value as an NWA at the primary feeder level of urban electricity distribution networks. We demonstrate the value of the developed framework by analyzing storage deployments in urban distribution feeders based
on conditions prevalent in Delhi, India.

India’s electricity demand is expected to increase rapidly, driven primarily by residential and commercial AC use and as well as electrification of transportation [6, 7]. Delhi is a city-state where 55% of electricity use is residential, that is more than double the national average (24%) [8]. The local distribution companies are witnessing increasing residential cooling demand that is overloading their network equipment well before schedule. Megacities such as Delhi are highly congested, and the regular activities of wire reconductoring or large equipment installation are operationally challenging, and in many cases, infeasible due to the region’s space-constrained geographical layout. This situation is not unique to Delhi; major cities worldwide are also experiencing a rise in electricity demand [9, 10, 11]. As another example, in Abuja, Nigeria, commercial customers are powered by off-grid diesel generation to meet demand when congested networks cause distribution-level outages. Distribution companies in Abuja compensate the off-grid operators for their diesel generators when their networks are constrained under negotiated contracts. Utilities in both countries frequently do not have the financial resources to upgrade their networks to meet the long-term forecasted peak demand. In case of Delhi, peak power demand in 2020 was 6.7 GW [12]. The variance between various growth and technology scenarios create a significant uncertainty in long-term demand growth [6] as seen in Table I. We focus on the deferral value that battery storage can provide in 2030 and 2040. The spread between these possible outcomes adds a large uncertainty factor to investment planning in the distribution networks.

Historically, long-term network planning by distribution companies has not
Table 1: Peak demand (GW) projections for baseline and high AC efficiency scenarios under medium GDP growth for the state of Delhi \[13\]

| Year | Baseline | High AC efficiency |
|------|----------|---------------------|
| 2020 | 6.7      | 6.7                 |
| 2030 | 12.7     | 15.2                |
| 2040 | 25       | 36.7                |
| 2050 | 34       | 63.8                |

considered uncertainty in forecasting but has instead resorted to deterministic net present value (NPV) methodologies \[14\]. While forecasts are not an accurate representation of the future, they provide a comparative assessment of program implementations such as appliance efficiency, policy design, and technology deployment. Nevertheless, given how large the gap between potential peak demand scenarios for a city similar to Delhi \[13\], probabilistic forecasting and flexible planning could be more relevant. This is particularly important when distribution companies incorporate using distributed energy resources (DERs) as an NWA. DERs are driven less by economies of scale because of their smaller size and their speed of implementation \[15\]. Up until recently, NWA in EMDE have predominantly been diesel generators that are deployed near large commercial and industrial (C&I) loads \[16\], but declining Li-ion battery storage costs \[17\] make it a more attractive DER to deploy. Moreover, battery storage provides the added advantage of not creating local air pollution, a major environmental externality in most megacities. Furthermore, depending on the energy source charging them, the carbon footprint of battery storage discharging to meet peak demand could also be lower than
diesel generation in most instances \[18\].

Existing literature on real options analysis of NPV of distributed generation and renewable energy highlight the benefits of options analysis to evaluate distributed generation investment \[19, 20\]. At the distribution level, diesel generators are the DERs that are considered. While options frameworks are developed for verifiable renewable energy (VRE), they are restricted to bulk power system level only. Moreover, these frameworks are developed using traditional NPV maximization rather than looking at cost standalone irrespective of revenue streams (which may be another layer of uncertainty in EMDE). Storage is increasingly studied and deployed at the distribution level for network expansion \[21\]. Real options analysis frameworks enable further VRE integration due to the flexibility they provide that a standard generation expansion planning framework cannot capture \[22, 23, 24\]. Nevertheless, while such studies focus on the developed countries, less work is done on EMDE \[25\], particularly at the distribution level where the conditions are particular to a cash-constrained environment and high growth in electricity demand in urban cities. Therefore, we present a real options analysis approach to assess the value of battery storage as a non-wire alternative at the distribution level based on cost and use of the battery.

Therefore, we couple previous findings of DER for NWA at distribution level and options analysis at bulk power system level to present a real options analysis approach that assesses the value of battery storage as a non-wire alternative at the distribution level based on cost and use of the battery. We make use of real options which provide better insight in decision-making and the ability to adopt a flexible strategy. Furthermore, we explore the role for
lithium-ion battery storage for short team peak demand shaving and network congestion relief. We develop a linear programming optimization that sizes each battery based on its hourly dispatch and the network’s thermal limit using a linearized network injection matrix. We define the value of flexibility based on the annualized investment and operational costs of the flexible NWA battery storage and the annualized investment cost in extensive network upgrades in current and future periods. We show that this approach enables identifying NWA battery storage options that decrease the present value of total investment cost in the context of distribution networks. Options are assessed based on a Markov Chain Monte Carlo simulation that quantifies the uncertainty in demand growth. The resulting flexible valuation framework is demonstrated by analyzing the storage NWA potential for distribution network feeders in Delhi and other megacities in India. We focus on testing the proposed framework in 2030 with further consideration for 2040 when the framework is applied at the city level.

2. Flexible valuation

Utilities may defer long-term investments by deploying battery storage to meet their short-term peak demand needs and mitigate short-term financial commitments. The NWA option provides utilities with the ability to wait and see how demand will grow. For an NWA battery storage system to be beneficial, the net present value of deferral of the lumpy investment must outweigh the NWA cost. This value can be computed as the difference between a traditional network upgrades investment now (period $y$) and a flexible investment now with a network investment later (in period $y + p$),
as shown in Eq. 1. Here, $OC_y$ is the option cost in period $y$ with flexibility until period $y + p$ and defined planning horizon $Y$, $AIC_{NET}$ is the annualized investment cost of traditional network investment, $AIC_{NWA}$ is the annualized investment cost of non-wire alternative investment, $FOM$ is the fixed operation and maintenance cost of the NWA battery, and $VAR$ is the variable battery charging cost at the available wholesale electricity tariff. When the cost of deferring traditional network investments from period $y$ to period $y + p$ with the cost of battery storage NWA throughout the time interval $p$ are lower than a traditional investment in period $y$, then that option to defer has value. In this case $OC_y$ is positive, signifying that a traditional investment is more costly than a flexible one. In Eq. 1 we compute the total investment cost as the sum of annualized investment cost ($AIC$) (defined in Eq. 2) over the planning horizon, so that multiple deferrals can be considered sequentially. This approach also allows us to account for the salvage value of the battery storage when the real option value of flexibility is no longer favorable (i.e. after its useful lifetime, which is equal to $p$ periods in Eq. 1).

The AIC computation for storage and network investment is based on total investment cost ($X_y$) made in period $y$ and the asset life ($L$). We assume a 15 year lifespan for battery storage and a 30 year lifespan for distribution network equipment. $WACC$ is the weighted average cost of capital (set to 9%), and the inflation adjustment is 2.5% (applied to technology cost projections). The total investment cost for traditional network upgrades is either wire reconductoring or transformer upgrade depending on the equipment being evaluated [26]. Battery storage cost is optimized based on loading data, power and energy capital costs [27, 17], and charge cost using a wholesale
Since demand growth is uncertain, the option cost computed via Eqn. 1 can be computed for alternative demand growth scenarios. Given demand forecasting uncertainty, we can price the option of flexibility with the annualized investment cost under each demand scenario and subsequently compute an expected value of the option based on the probabilities for each demand scenario.
scenario. Specifically, we sampled the expected value $p$ of a demand scenario in a given period from the predicted posterior distribution of decadal growth in electricity demand using the Markov Chain Monte Carlo method. Each demand growth scenario will have a sampled conditional probability, and the following equation then governs the decision-making process:

$$D_{y,y+p} = p_{\text{low}} \cdot OC_{\text{low},y,y+p} + p_{\text{mid}} \cdot OC_{\text{mid},y,y+p} + p_{\text{high}} \cdot OC_{\text{high},y,y+p}$$  \hspace{1cm} (3)$$

We restrict the options analysis to three demand projections based on low, mid, high growth in electricity demand to simplify possible growth scenarios. $D$ is the option cost given three scenario projections and their predicted probabilities. If $D < 0$, then the expected cost of storage and network upgrade deferral is lower than traditional network upgrades, and therefore storage has a non-negative NWA value. The process is repeated at every decision point $p$ with the corresponding cost, projections and probabilities, as illustrated in Fig. [Fig. 1].

3. Model Description

The modeling to compute network upgrade and NWA related costs in Eq. [Eq. 1] that governs the flexible valuation framework is divided into three parts: placement, sizing and, simulation as seen in Fig. [Fig. 2]. First, we identify the optimal location to relieve the distribution network from overloading. Congestion occurs primarily during peak hours because of high simultaneity in demand for electricity, implying that various component of the network overload simultaneously. This will enable us to estimate the cost of traditional network upgrades that may be deferred. The optimal storage location
is identified to relieve the greatest demand on the feeder from a minimum number of locations. Second, we evaluate the cost-optimal sizing of the battery storage system at the identified location for a given demand scenario, depending on the hourly load profile and the thermal limits of the network components. A time-series linear program is used to size the system for the various demand growth scenarios. The optimizations identify the capacity of battery storage to be deployed, from which we infer the capital and operating cost of battery storage. This second step is repeated for the various considered demand growth scenarios (low, medium, high). The final part of the model is the simulation of various posterior probabilities of demand growth to identify the cost-saving option value of NWA and network deferrals using Markov Chain Monte Carlo.
3. Battery storage placement

The storage placement optimization is governed by the network sensitivity matrix to optimize for maximum feed-in (battery charging potential) and out (battery discharging potential). We identify the nodal power injection potential using the linearized sensitivity matrix described in [30]. The sensitivity (injection) matrix \( s \) is based on the power flow Jacobian matrix [31] and reveals the relationship between bus voltages and bus power injection. The sensitivity matrix services as the constraining matrix of flow limitation [30].

\[
\begin{bmatrix}
\Delta V \\
\Delta \theta 
\end{bmatrix} =
\begin{bmatrix} s \end{bmatrix} \times
\begin{bmatrix}
\Delta P \\
\Delta Q 
\end{bmatrix} 
\tag{4}
\]

\( \Delta P \) refers to real power deviation, \( \Delta Q \) refers to reactive power deviation, \( \Delta V \) refers to bus voltage magnitude deviation and \( \Delta \theta \) refers to bus voltage angle deviation. Due to higher resistance cables at the distribution level, we can limit the optimization to real power injection impact on voltage deviation and ignore the \( \Delta Q \) and \( \Delta \theta \) elements. The relationship described
in Eqn. 4 is simplified and expanded to become:

\[
\begin{bmatrix}
\Delta V_1 \\
\Delta V_2 \\
\vdots \\
\Delta V_N \\
\end{bmatrix} = \begin{bmatrix}
\frac{\partial V_1}{\partial P_1} & \frac{\partial V_1}{\partial P_2} & \cdots & \frac{\partial V_1}{\partial P_N} \\
\frac{\partial V_2}{\partial P_1} & \frac{\partial V_2}{\partial P_2} & \cdots & \frac{\partial V_2}{\partial P_N} \\
\vdots & \vdots & \ddots & \vdots \\
\frac{\partial V_N}{\partial P_1} & \frac{\partial V_N}{\partial P_2} & \cdots & \frac{\partial V_N}{\partial P_N} \\
\end{bmatrix} \times \begin{bmatrix}
\Delta P_1 \\
\Delta P_2 \\
\vdots \\
\Delta P_N \\
\end{bmatrix}
\]  

(5)

Each element \(\frac{\partial V_i}{\partial P_j}\) in the linearized sensitivity matrix as the sum of resistances of the lines of the path \(PT_{ij}\) connecting node \(i\) to node \(j\). Since we are dealing with radial distribution networks [30, 32], this linearization is a faster method to finding sensitivity relationships between nodal voltage and power injection as described in Eqn. 6

\[
\frac{\partial V_i}{\partial P_j} = -\frac{1}{V_{\text{base}}} \sum_{hk \in PT_{ij}} R_{hk}
\]

(6)

Using the system of equations described in Eqn. 5 we can build two separate optimization models that will help us isolate the optimal storage location on the network. We wish to identify the maximum power withdrawals during off-peak times and maximum injections during peak times while minimizing voltage variations. The first model solves for maximum power withdrawal from the network in off-peak demand periods, when storage will be charging from the grid, while keeping voltage deviation to be as low as possible (objective function) and maintaining all bus voltages within the defined boundary (constraint). The second model solves the maximum power injection into the network during the peak demand periods while using the same objective function and constraints as above. This is translated to the linear program
described in Eqn. 7. Where $LV_B$ and $UV_B$ are the steady-state lower voltage boundary and upper voltage boundary, respectively. $E_i$ is the voltage at bus $i$ before DER injection. We set the bounds within a +/- 5% margin as per industry standard. The optimization models for off-peak and peak times only differ by the $[s]$ matrix that is extracted from a priori power flow simulation for the off-peak and peak demand at the buses.

$$\min_{\Delta P_y} \sum_x ||\Delta V_x||$$

s.t. 

$$\begin{bmatrix} \Delta V_1 \\ \vdots \\ \Delta V_i \end{bmatrix} = \begin{bmatrix} \frac{\partial V}{\partial P_1} & \cdots & \frac{\partial V}{\partial P_j} \\ \vdots & \ddots & \vdots \\ \frac{\partial V_i}{\partial P_1} & \cdots & \frac{\partial V_i}{\partial P_j} \end{bmatrix} \begin{bmatrix} \Delta P_1 \\ \vdots \\ \Delta P_j \end{bmatrix}$$

$$LV_B \leq \begin{bmatrix} E_1 - \Delta V_1 \\ \vdots \\ E_i - \Delta V_i \end{bmatrix} \leq UV_B$$

$$x \in (1, i)$$

$$y \in (1, j)$$

With the additional constraint $\Delta P_j \geq 0$ for the off-peak scenario representing storage as a new load withdrawing power from the bus and $\Delta P_j \leq 0$ for the peak scenario representing storage as a new static generator injecting power into the bus. The storage placement optimization storage is implemented in the open-source Python package Pyomo [33] and the CPLEX solver [34] which permit the simple formulation and optimization of the linear mathematical programs in a matter of seconds on a personal computer.
3.2. Battery storage optimization

When considering NWA battery storage, cost drives the planning process [35]. We develop a linear programming optimization that sizes the battery storage for a given equipment’s hourly load profile and thermal limit. The equipment can be any element of the distribution network that is overloading and requires reinforcement. The battery storage investment cost is broken down by energy and power as per Table 2. We restrict the case to lithium-ion storage (Li-ion) for data and commercial availability purposes.

3.2.1. Parameters

- \( N \): number of time intervals — 168
- \( \Delta t \): time step — 1 hour
- \( I = \{1, \ldots, N\} \): time interval
- \( L = [L_1, \ldots, L_N] \): load vector in kW, with \( L_k \) being the demand during the \( k^{th} \) time interval
- \( C = [C_1, \ldots, C_N] \): wholesale electricity tariff vector, with \( C_k \) being the cost of electricity during the \( k^{th} \) time interval — Table 2
- \( Z = [Z_1, \ldots, Z_N] \): energy stored in the battery, with \( Z_k \) being the energy stored in the battery after the \( k^{th} \) time interval
- \( c_{\text{power}} \): battery power cost in USD/kW — Table 2
- \( c_{\text{energy}} \): battery energy cost USD/kWh — Table 2
- \( S_{\text{max}} \): size of the battery in kWh — maximum charging capacity throughout the number of time intervals
• $Q_{\text{MAX}}$: maximum allowed rate of charge — difference between max peak and component limit

• $Q_{\text{MIN}}$: minimum allowed rate of discharge; $Q_{\text{MIN}} = -Q_{\text{MAX}}$

• DoD: depth of discharge of the battery — 90%

• $e$: round-trip efficiency — 85%

3.2.2. Variables

• $x = [Q, Q_{\text{bat}}]$ where $Q = [Q_1, \ldots, Q_N]$: power vector of the kW battery power, with $Q_k$ (real) being the power during the $k^{th}$ interval and $Q_{\text{bat}}$ (non-negative real) is the battery’s maximum rate of charge and discharge

• $y = |S|$ where $S$ (non-negative real) is battery capacity to be installed in kWh

• $Z_0$ (non-negative real) is initial energy stored in the battery

3.2.3. Objective function

$$\sum_N ((L + Q)^T \cdot C) + c_{\text{power}} \cdot Q_{\text{bat}} + c_{\text{energy}} \cdot S$$  \hspace{1cm} (8)

3.2.4. Constraints

Demand balance.

$$L_k + Q_k \leq P_{\text{max}} \quad \forall k \in I$$  \hspace{1cm} (9)
Minimum battery capacity.

\[(1 - \text{DoD}) \cdot S_{\text{max}} \leq e^{\Delta t} \left( Z_0 + \sum_{i=1}^{k} Q_i \right) \quad \forall k \in I \quad (10)\]

Maximum battery capacity.

\[e^{\Delta t} \left( Z_0 + \sum_{i=1}^{k} Q_i \right) \leq S_{\text{max}} \quad \forall k \in I \quad (11)\]

Minimum charge rate.

\[-Q_k - Q_{\text{bat}} \leq 0 \quad \forall k \in I \quad (12)\]

Maximum charge rate.

\[Q_k - Q_{\text{bat}} \leq 0 \quad \forall k \in I \quad (13)\]

Lower and upper bounds.

\[\max(Q_{\text{MIN}}, -L_k) \cdot y \leq x_k \leq Q_{\text{MAX}} \cdot y \quad \forall k \in I \quad (14)\]

Initial energy stored.

\[Z_0 \leq S_{\text{max}} \quad (15)\]

\[Z_0 \geq (1 - \text{DoD}) \cdot S_{\text{max}} \quad (16)\]

3.3. Markov Chain Monte Carlo

With the battery storage optimization, we can size the storage energy capacity and power needed for NWA network upgrades for each of the different
demand growth projections. Scenario growth probability is needed to weigh the different options and identify the investment decision. We do so by leveraging statistical modeling. A Bayesian model comprises two main parts: a statistical model describing the distribution of the data and a prior distribution describing beliefs about the unknown. The posterior is then derived using these two parts. Markov Chain Monte Carlo (MCMC) simulations enable estimating parameters such as mean, variance, expected values of the posterior distribution of a Bayesian model. Random values are sampled from the prior using a transition kernel to assess the parameters of the desired distribution. The transition kernel is split into two steps: a proposal step and an acceptance/rejection step. Given $\pi$ as an approximate prior distribution, $q$ as the proposal distribution, and $p_{acc}$ as the acceptance criteria, the complete Metropolis-Hastings transition kernel can be written as follows:

$$T(x_{i+1}|x_i) = \begin{cases} 
q(x_{i+1}|x_i) \cdot p_{acc}(x_{i+1}|x_i) & : x_{i+1} \neq x_i \\
1 - \int dx_{i+1} q(x_{i+1}|x_i) \cdot p_{acc}(x_{i+1}|x_i) & : x_{i+1} = x_i 
\end{cases}$$  \hspace{1cm} (17)

With the acceptance probability as:

$$p_{acc}(x_{i+1}|x_i) = \min \left\{ 1, \frac{\pi(x_{i+1}) \cdot q(x_i|x_{i+1})}{\pi(x_i) \cdot q(x_{i+1}|x_i)} \right\}$$  \hspace{1cm} (18)

Given three scenarios on electricity demand growth up to 2050, we use MCMC Metropolis-Hastings (MH) to estimate the expected values of demand growth on a decadal basis using a Poisson distribution to define the likelihood function and $\Gamma$ distribution to define the proposal distribution.
We parametrize the shape and scale of the $\Gamma$ prior with the mean $\mu$ and variance $\sigma$ as per Eqn. [19]

\[
\text{Growth} \sim \text{Pois}(\lambda) \quad \lambda \sim \Gamma(a, b) \quad a = \frac{\mu^2}{\sigma^2} \quad b = \frac{\mu}{\sigma^2}
\]  

(19)

$\pi$ is represented by historical data; however, it is incomplete due to limited data points. Therefore, direct sampling from $\pi$ is not possible. The Monte Carlo simulation part of the MCMC enables us to run the MH algorithm enough times to converge to a stationary distribution by running multiple chains simultaneously to avoid burn-in bias [37]. The result of the MCMC simulation is a posterior distribution function that we use to evaluate the conditional probabilities of growth.

4. Results

The flexible valuation framework is designed to inform decisions on network upgrades under high growth and high uncertainty in electricity demand projections. An faster than anticipated increase in electricity demand will prematurely overload the electric grid forcing distribution companies to either shed load or invest in traditional network upgrades. We apply the flexible valuation framework model described above to an urban feeder in Delhi under an available set of projections [13] for the 2030 period. Subsequently we assess distribution level storage potential in other megacities in India (Mumbai, Bengaluru, Kolkata) with different demand and network characteristics and compare how these impact the role for battery storage as an NWA. To model distributed storage integration on the network, we use a benchmark
medium voltage distribution network [38] and adapt the network equipment — line, transformer, voltage, current — to model the collected data from Tata Power Delhi Distribution Limited [39] primary distribution 33 kV and 11 kV network.

4.1. Urban feeders — Delhi, India

The 2 MW network is divided into three feeders leaving the distribution substation: residential, commercial, and industrial, with the residential load being the dominant one (80% of the substation load is residential). The residential feeder initially has an average loading of 50% [39]. As per section [39], the

Figure 3: Distribution network diagram: three main feeders: commercial (top), industrial (middle), residential (bottom). Bus number in **bold** and line number in *italic*
we start by identifying the optimal locations for storage on the distribution network (Fig. 3) with the load projection of the next investment period \( p = 1, 2, 3, \ldots \). For the next step, as detailed in section 3.2, we size storage considering the hourly demand profile that is perceived on the bus of choice and derives the cost of storage under different projections. Finally, the result of the MCMC simulation of section 3.3 yields the probabilities necessary to inform the real option of NWA storage compared to traditional network upgrades.

4.1.1. Battery storage placement

![Diagram of storage placement optimization result on buses and line loading](image)

Figure 4: Storage placement optimization result on buses and line loading

When the network is overloaded, bus voltage will drop. Therefore, the storage placement optimization described in Eqn. 7 yields maximum bus injection on the network buses since the sensitivity (or injection) matrix is used as the constraint for minimum voltage deviation while maintaining all bus voltages within the defined boundary. Buses with the highest possible injection are
the locations with the most flexibility to deploy storage. When limited to
the choice of three buses, the highest-ranking ones are 7, 22 and, 28 for com-
cmercial, industrial, and residential feeders, respectively. Fig. 4 illustrates
the impact on bus voltages. Also, since storage placement is designed to
reduce congestion, Fig. 4 shows that its deployment reduces line loading.
Since the network is mainly residential-loaded starting from bus 24, the im-
pact of installing storage on bus 28 is significant, as seen at the downstream
bus voltage (28 to 43). Similarly, line loading percentage is reduced to an
acceptable level, particularly on lines 1 and 26 (marked in red in Fig. 3),
which are the main trunks of the residential feeder.

4.1.2. Battery storage sizing

We further investigate the residential bus 28 to size the storage system. The
main trunk of the residential feeder has a capacity of 850 kW; however, peak
demand is expected to overload the feeder between 2025 and 2035, depending
on growth projections. Using the linear program described in section 3.2, we
evaluate a five-year deferral option and, therefore, size the battery accord-
ingly. The time-series optimization yields the dispatch behavior illustrated
in Fig. 5 where storage is charging during off-peak hours without violating
the thermal limit of the feeder and is discharging during peak hours when
demand would overload the feeder. For cost assumptions noted in Table 2.
The solution is a 2.1 MWh battery capacity with 380 kW discharge power,
i.e., a 5.5 hours storage duration. The above-described linear mathematical
program that sizes battery storage is formulated using the week with the
highest peak demand. Similarly to section 3.1, the optimization model is
formulated in Pyomo [33] and solved using CPLEX [34].
We project three growth scenarios and estimate the traditional, deferred, and NWA upgrade size and cost. Given Table 2 and Eqn. 2, the lithium-ion battery storage system non-wire alternative annualized investment cost are shown in Table 3.

| Growth  | Power (kW) | Capacity (kWh) | AIC (USD-year) | FOM (USD-year) | Charge (USD-year) |
|---------|------------|----------------|----------------|----------------|------------------|
| Low     | 300        | 1,200          | 8,358          | 6,000          | 4,950            |
| Medium  | 380        | 1,520          | 10,586         | 7,600          | 8,778            |
| High    | 420        | 1,680          | 11,701         | 8,400          | 12,474           |

Table 3: Storage sizing optimization results and resulting costs of battery storage. Battery storage life is 15 years and WACC is set to 9%

Using table 2 and Eqn. 2 we calculate the AIC for the traditional and
five years deferred network upgrades. We run static power flow simulations (Newton-Raphson method) using the python package pandapower. Without storage, the power flow simulations results in 3 kilometers of line upgrades required under medium growth projections. Moreover, 2 and 4 kilometers would require upgrades under low and high growth projections, respectively. Power flow simulations are also run to verify that the deployment of battery storage on the network reduces overloading on the feeders as per example Fig. 4.

| Traditional network upgrade AIC (USD) | Low       | Medium    | High      |
|--------------------------------------|-----------|-----------|-----------|
| Low                                  | 14,673    | 22,009    | 29,345    |

| Deferred network upgrade AIC (USD)   | Low       | Medium    | High      |
|--------------------------------------|-----------|-----------|-----------|
| Low                                  | 12,969    | 19,453    | 29,937    |

Table 4: Network upgrades results

4.1.3. Real options analysis

Now that all the cost terms to compute the option cost defined in Eqn. 1 are available, we can evaluate the option of deferring network upgrades for five years by installing lithium-ion battery storage up to 2025 to meet peak demand. To do so, we evaluate the probability of demand growth as described in Eqn. 3. Estimating electricity consumption growth to meet target decadal electricity demand projected in [13] requires posteriori knowledge, for which rely on electricity consumption trends in the Chinese context. While China has achieved faster growth than India in the past four decades, as seen in Fig.
6a. it is anticipated that India will experience high growth [6] where India is expected to account for 22% of global cooling demand in 2050. Moreover, Fig. 6a positions India two decades behind China in electricity consumption per capita. Evidently, historical Chinese electricity consumption growth is not complete data to directly sample from as prior information on future electricity consumption in India. Therefore the Chinese data is used as prior distribution in the MCMC simulation to generate the posterior distributions for decadal growth in electricity consumption for India. China’s historical electricity consumption per capita can be visualized as distribution functions modeled historical growth rates for all years (Fig. 6b) and on a decadal basis (Fig. A.9). As mentioned in section 3.3 we model electricity consumption growth rate by a Poisson distribution with parameter $\lambda$ and a gamma distribution for the prior. After empirical investigation to achieve an acceptance rate $p_{acc}$ higher than 80% in the MCMC simulation, we impose the shape and scale parameters (Eqn. 19) of the $\Gamma$ prior distribution to be set as per Eqn. 20.

$$\mu \sim \Gamma(2, 0.2) \quad \sigma = e$$

(20)

For each decadal growth, we run three chains to eliminate any burn-in bias. Chain results and convergence evidence is highlighted in Fig. A.10 and Table A.9. Given the simulation results, we can derive predictions. Projecting growth to 2050 requires predictions on growth over the next three decades: 2020’s, 2030’s, 2040’s. As previously mentioned, the first two decades are assumed to be known as per the synergies with historical growth rates in
Figure 6: Historical electricity consumption patterns for China and India that is used to develop prior distributions for the MCMC simulations

China. We use the Poisson distribution using the MCMC accepted values of $\lambda_{2020}$ and $\lambda_{2030}$. For the final decade, we use the MCMC accepted values of $\mu$ and $\sigma$ to construct $\Gamma$ and subsequently identify $\lambda_{2040}$ as per Eqn. 19 and 20. The resulting posterior distributions are plotted in Fig. 7. Finally, sampling from these posterior distributions will inform the likelihood of growth throughout each decade.

Figure 7: Estimated posterior distributions of projected growth in electricity consumption for India by decade

Per prior analysis 41 low growth is defined as an annual growth rate less than 5% while high growth is defined as an annual growth rate higher than
7% and in between is considered medium growth for India. The result of the MCMC transition kernel is represented in Table 5 columns 1 and 2. Using Eqn. 3, we identify the real option value of each transition in column 3 of Table 5. The option value is positive for the medium and low demand growth scenario, which means that deferral of network upgrades by NWA battery storage is cheaper than traditional network upgrades on expectation. The result of the different options aligns with the motivation of the flexible valuation framework. If demand realizes under high growth, it is cheaper to upgrade the network immediately. However, the flexibility of NWA battery storage allows the utility to adopt a ”wait and see” strategy and benefit from lower than anticipated growth to defer upgrades. For this reason, the option value of low projection is the highest, and the high one is the lowest (negative).

Finally, we can construct Eqn. 3 to inform the decision on whether to upgrade the main trunk on Bus 28 or place storage and defer investment. We simulate peak demand growth by sampling from the posterior distributions for the 2020 decade. Investment planning is triggered one time period before overloading is expected given the expected growth projection, i.e., as we sample demand on the main trunk of Bus 28, we project maximum peak demand using the growth forecasts [13] that corresponding to the present period’s growth. This allows us to discretize expected peak demand values by constantly optimizing the upper bound and avoiding any load shedding. As seen in Fig. 8, which considers medium demand growth projections, as per Table 5 real option values, 2025 will trigger the options analysis for the period 2030 since we can expect the feeder to overload in 2030 given how
| Growth step    | Option cost (USD) | Probability | Real option value (USD) |
|--------------|-----------------|-------------|------------------------|
| Medium-Low   | 36,328          | 38%         |                        |
| Medium-Medium| 15,864          | 32%         | 20,679                 |
| Medium-High  | 5,632           | 30%         |                        |
| Low-Low      | (1,361)         | 34%         |                        |
| Low-Medium   | 36,328          | 33%         | 35,692                 |
| Low-High     | 74,018          | 33%         |                        |
| High-Low     | (32,057)        | 20%         |                        |
| High-Medium  | 5,632           | 80%         | (24,519)               |
| High-High    | 43,322          | 0%          |                        |

Table 5: Real options analysis for main trunk of bus 28 noted in the residential feeder in Fig. 3

demand has grown from 2020 to 2025 under medium growth trajectory considered in this case. The battery is sized and installed in 2030. It serves to increase the capacity of the main trunk up until 2035, which is when the deferred network upgrades are installed to meet projected peak demand up to 2045 (the last period in the real options analysis).

While we limit the results to \( p = 5 \), the real option value will differ based on cost, growth projections, probabilities, and longevity of investment deferral. When \( p \) is increased, the real option value becomes negative, meaning storage cannot defer network upgrades for more than five years since the increase in the cost of storage due to both the larger system required and the larger annual investment cost of storage does not justify the financial deferral value.
Figure 8: Real options model analysis simulation time series as per Fig. 1 with low, medium and high demand growth projections scenarios. $y = 2020, Y = 20$, four timesteps $p$ of 5 years intervals as per the input projected data [13].

of traditional network upgrades. The deferral value is positive in the Indian context and more broadly in EMDE due to the higher discount rates in those countries compared to other regions like the U.S.. Trivially, a lower discount rate will favor traditional network upgrades. Moreover, since power is mostly contracted in Delhi, we do not consider the potential value of arbitrage that distribution-level NWA storage can offer utilities if market conditions exist. So it is important to note that while NWA storage is utilized for only peak hours of the year, it can be more actively deployed and have a higher value than traditional network upgrades that do not have multiple use cases.
4.2. Potential for storage in Indian megacities

We identify four megacities of India, Delhi, Mumbai, Bengaluru, and Kolkata, that collectively accounted for 52 TWh of electricity consumption in 2019 and an estimated 72,763 circuit kilometers of distribution lines at 33 and 11 kV serving dense urban areas by their respective utilities [42, 43] (see Table [6]). We apply the flexible valuation framework on these four megacities to identify India’s distribution-level storage capacity estimate. Due to data scarcity, we define nine representative feeders via clustering from a library of urban feeders (and their corresponding hourly load profiles) for the city of Delhi serviced by Tata Power Delhi Distribution Limited (TPDDL) [39]. Each representative feeder is characterized by:

1. Loading percentage varying from 40 to 80%
2. Represented demand: hourly load profile that corresponds to a representative feeder, varying by megacity according to further surveyed data [44]
3. Serviced demand: total demand (MWh) that is serviced by a distribution network with the same loading percentage
4. Serviced circuit kilometers: total circuit kilometers with the same loading percentage

The collected data from the city of Delhi shows that 28% of feeders are loaded at 60% or more on an ampere capacity basis as of 2018. We assume the same loading distribution for the other megacities as observed in Delhi. We calculate the ratio of demand (MWh) to circuit kilometers for each representative feeder in the city of Delhi and apply it to the other megacities’ representative
feeder serviced demand to derive the serviced circuit kilometers for each representative feeder. We sequentially apply the flexible valuation framework on each representative feeder for each megacity by using the appropriate demand projections available from [13]. A representative feeder’s resulting storage energy capacity is scaled up using the serviced demand to represent the demand ratio. Given scaled storage energy capacity and serviced circuit kilometers, we identify the network investment and NWA costs used to define the option cost. While demand projections are available up to 2050 [13], large uncertainty in technology cost diminishes the value of the flexible framework; therefore, we restrict the simulations to 2030 and 2040. As part of our sensitivity analysis, we also consider alternative cost trajectories of lithium-ion battery storage [27]. Finally, as noted earlier, since electricity is mostly contracted in Delhi and other cities in India, we do not consider the value of energy arbitrage that NWA storage may offer.

Table 6: Megacity-level DLS potential (GWh) as an NWA under mid-range cost projections

| City     | 2019 Demand (TWh) | Overloaded circuits (km) | DLS potential (GWh) | Overloaded circuits (km) | DLS potential (GWh) |
|----------|-------------------|--------------------------|---------------------|--------------------------|---------------------|
| Bengaluru | 10                | 1,265                    | 3                   | 1,467                    | 15                  |
| Delhi    | 23                | 6,093                    | 14                  | 7,070                    | 50                  |
| Kolkata  | 4                 | 792                      | 1                   | 919                      | 35                  |
| Mumbai   | 15                | 12,224                   | 11                  | 14,184                   | 40                  |
Given current loading percentage and load projections, we estimate 20,373 km will be overloaded — line loading over 80% for more than 4 hours per day — in 2030 and an additional 23,640 km in 2040. Table 8 shows the alternative cost assumptions for distribution-level lithium-ion battery storage [27, 28] used in the flexible valuation framework. When the flexible valuation framework is applied on the representative feeders and then scaled back to the total demand they represent, we estimate it is cost-effective to install a total of 29 GWh and 140 GWh of short-duration storage (5-6 hours) to defer 15,914 and an additional 18,127 km of network upgrades for 2030 and 2040, respectively. These results correspond to the low and mid-range cost assumptions for Li-ion storage. When considering the multi-period investment, storage deployment before traditional network upgrades produces 16% capital investment savings in 2030 and 15% in 2040 as seen in Table 7. More storage is deployed in 2040 per unit kilometers than 2030 due to the increasingly peaky nature of the projected demand [13]. In these calculations, storage is assumed to remain present on the system as long as it is dispatchable since the longer it remains on the feeder, the more value it defers.

The optimization of section 3.2 is constrained by hourly dispatch; subsequently, the real options analysis is constrained by cost. We further investigate the impact of storage cost on the viability of NWA storage. Table 6 summarizes the result of the megacities’ potential under the various cost projections. The flexible valuation framework yields similar results for low-cost storage [27]; this indicates that the only binding constraint is dispatch, i.e. the ability of storage to charge during off-peak demand periods. Further-
Table 7: Flexible valuation framework aggregate results for medium growth demand projections

| Cost Object (in Millions of 2020 USD) | 2030  | 2040 |
|--------------------------------------|------|------|
| DLS                                  | $207 | $261 |
| Annualized deferred upgrades         | $76  | $136 |
| Annualized traditional upgrades      | $117 | $133 |
| Total flexible budget                | $2,932 | $5,324 |
| Total traditional budget             | $3,503 | $6,266 |

more, NWA is occasionally not viable for heavily loaded feeders due to a lack of off-peak hosting capacity for battery charging (i.e., the feeder is already close to overloading, and there is little uncertainty about demand growth, as illustrated in the high demand growth case in Table 5). On the other hand, under high storage cost, 11,752 km and 13,717 km of network upgrades are selected for deferral, producing 12% and 10% capital investment savings in 2030 and 2040, respectively. This result implies that under higher costs of storage assumption, more NWA options become expensive and therefore trigger traditional network investment instead. Applying a cost sensitivity yields a breakeven cost of storage at 262 USD/kWh for the remaining cost and performance assumptions considered for the Indian context.

As detailed earlier, NWA is driven by capital investment savings for utilities rather than the competitiveness of storage as a resource. The attractiveness of storage as an NWA in network-constrained environments where utilities have short-term financial commitments has a proliferation potential. However, it requires further assessment at transmission and capacity expansion
Table 8: Storage cost impact on outputs of the flexible valuation framework applied to the four Indian megacities, for year 2030. Low, mid and high storage cost assumptions are sourced from [27].

|                                | Low  | Mid  | High | Breakeven |
|--------------------------------|------|------|------|-----------|
| Storage energy cost (USD/kWh)  | 116  | 168  | 236  | 261       |
| Storage power cost (USD/kW)    | 101  | 146  | 205  | 227       |
| DLS energy capacity (GWh)      | 29   | 29   | 18   | 0         |
| Deferred upgrades (km)         | 15,914 | 15,914 | 11,752 | 0         |

levels to quantify its net impact on the overall system. The battery must be charged in the day, and in EMDE where coal [45] is the dominant baseload generation, the long-term cost and environmental benefits may not outweigh the short-term cost benefits at the distribution level.

5. Discussion

The flexible valuation framework relies solely on cost objects and not on revenues which subsequently evaluate NPV. The main reason is that utilities are generally allowed to charge a reasonable rate of return to justify their cost object, and therefore NPV will always be positive if justified. Moreover, utilities in EMDE are primarily concerned with capital allocation owing to relatively high cost of financing. We highlight the usefulness of using cost objects for the options analysis through capital utilization rates (CUR). CUR is defined as the ratio of actual output to maximum output potential. In the case of network equipment, CUR is the ratio of equipment loading in a given
period $D_{t,y}$ to equipment thermal limit $M_t$. 

\[ CUR_{t,y} = \frac{D_{t,y}}{M_t} \]  

(21)

A higher capital utilization rate means the capital is being better allocated. Referring back to the results of the options analysis on the primary trunk of bus 28 (Table 5), we note a CUR for the deferred network investment of 76, 59, 47 percent for low, medium, and high growth projections, respectively. CUR percentages for the traditional network investment are 70, 53, 41 percent for low, medium, and high growth projections. Thus, this shows by adopting a cost-based option valuation framework, we improve the capital utilization rate of utilities. Additionally, utilities in EMDE face shorter-term financial commitments [4] due to a lack of long-term loan availability. Improving CUR will therefore serve utilities better to recover their investment and fulfill their financial commitments.

Moreover, on a simple system cost of electricity basis (Eqn. 22), the flexible option of deferring investment has a system cost of electricity of 0.28 USD/MWh in 2030 and 0.36 USD/MWh in 2040 for the ten years. The traditional network investment option has system costs of 0.46 and 0.42 USD/MWh in 2030 and 2040. From a system cost perspective for the 20 years framework, annualized capital investment savings are 27%. However, when aggregating NWA distribution storage to the transmission level for national planning considerations, the impact on the overall system cost of electricity may not be strictly positive. Depending on which resource is charging the NWA storage, there is a potential for power system cost increase in countries
that heavily depend on coal generation, such as India.

\[
Systemcost = \frac{Totalannualizedcostofstorage}{Totalannualshaveddemand}
\]  

(22)

6. Conclusion

The flexible valuation framework presents a novel approach based on cost comparison of the various wire and non-wire alternative upgrade schemes using real options analysis. We have employed optimization tools that enable the calculation of the cost objects used to compute the option cost. We develop a simulation model based on Bayesian statistics for sample growth uncertainty to evaluate different options under various projections. The result is a decision-making framework for distribution network investment that takes into account uncertainty in demand growth.

We show that the flexible valuation framework enables the utility to minimize its present investment amount and defer lumpy investments to future times of more certainty on growth. We conclude that under high uncertainty and volatility of growth projection, the flexible valuation framework has a higher upside to installing battery storage as NWA since peak demand was overestimated in prior periods. Thus traditional upgrades can be further deferred into the future. Furthermore, distribution level congestion is an increasingly common problem across urban areas in EMDE such as India. We utilize the flexible valuation framework and representative feeders across various metropolitan areas in India to estimate the distribution-level storage potential. The flexible valuation framework enables utilities to adopt a
wait and see strategy with minimal investment cost when there is high uncertainty about future demand growth. NWA battery storage can be considered a zero-cost peak shifting mechanism at the transmission level to assess the supply-side impact. Added value from arbitrage and other ancillary services typical to storage increases storage value as an NWA.

Appendix A. Figures and Tables

![Box plot of Chinese annual growth rate grouped by decades](image)

Figure A.9: Box plot of Chinese annual growth rate grouped by decades

|        | mean | sd   | hdi 3% | hdi 97% | mcse mean | mcse sd |
|--------|------|------|--------|---------|------------|---------|
| $\mu$  | 7.113| 1.15 | 4.933  | 9.333   | 0.027      | 0.019   |
| $\sigma$ | 2.087| 0.834| 0.774  | 3.568   | 0.022      | 0.015   |
| $\lambda_{2020}$ | 5.86 | 0.738| 4.464  | 7.246   | 0.016      | 0.011   |
| $\lambda_{2030}$ | 6.117| 0.757| 4.802  | 7.657   | 0.015      | 0.011   |
| $\lambda_{2040}$ | 10.562| 1.089| 8.564  | 12.645  | 0.026      | 0.018   |

Table A.9: MCMC simulation result summary. sd: Standard Deviation, hdi: High Density Interval, mcse: Markov Chain Standard Error
Figure A.10: Trace plots of MCMC simulation (sampling distribution to the left, simulation to the right) of the shape (top plots) and scale (middle plots) of the $\Gamma$ distribution and the Poisson distribution parameter (one $\lambda$ distribution per decade). Convergence is visually inspected from the bounded MCMC simulation results.

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