Distribution Systems Planning and Analysis Framework for Indian Feeders

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***Abstract*—Integration of distributed energy resources (DER) such as photovoltaics, electric vehicles (EVs) and battery energy storage systems (BESS) is expected to rapidly increase in distribution systems in India. These grid edge resources can have adverse impacts on the grid and can provide additional revenue streams as well. To mitigate these impacts distribution planning and analysis is required. So this paper presents a framework which can be used to complete all steps involved in distribution planning and analysis. This framework uses data in the same format as is readily available with Indian utilities and processes it to generate detailed feeder models and loading profiles. This framework already includes multiple DER use cases such as peak shaving for BESS and EV demand modelling and can be easily extended to simulate a number of additional use cases. All of these use cases can be simulated in parallel for multi-year time series simulations using an integrated command line interface. A suit of grid readiness metrics are then evaluated for each simulation to determine required network upgrades and associated costs.**

***Index Terms*—Distribution grid issues; electric vehicles; power system studies; project experience**

I. Introduction

The bulk power system is undergoing a major transformation with the integration of distributed energy resources (DERs) such as photovoltaic systems, battery energy storage systems (BESS) and more recently electric vehicles (EVs). Grid integration of EVs pose unique challenges. EV charging, especially from DC fast chargers, can act as a large intermittent distribution-connected load which might necessitate grid infrastructure upgrades. To mitigate the grid impact of EVs and other DERs, distribution system planning and analysis is essential. This paper presents a comprehensive and easily extendable platform developed to conduct this analysis starting from the available raw data from an Indian utility to accurate year-long time series analysis for different DER use cases.

Developing detailed and validated distribution feeder models is crucial before any distribution system impact study may be conducted. A lot of research has been done on the development of detailed feeder models [1], [2]. However, many times these models only include the primary network and not the secondary or the low voltage (LV) networks. These models might be sufficient for some types of studies but these cannot capture local parameters such as customer nodal voltages. modelling the secondaries becomes even more critical for Indian feeders as each distribution transformer (DT) caters to hundreds of customers via longer LV lines unlike North American feeders which cater to 5-15 customers through relatively shorter secondary lines. modelling distribution feeders is challenging as line transposition and balanced phase loading cannot be assumed and all the phases of each feeder component have to be modeled accurately [3].

Conducting distribution planning studies can be challenging when the feeders are prone to be afflicted by outages more frequently. Moreover, the metering/sensing equipment can struggle to keep pace with the relatively rapid evolution of the topology of these distribution systems. Thus, the distribution transformer loading profiles-those essential for power flow analysis of an electrical distribution network-can also be afflicted by a host of inconsistencies which must be addressed to enable power flow studies. So, section II of this paper presents a method developed for generating distribution feeder models and for optimally allocating the loads using the Geographical Information Systems (GIS) and meter data provided by an Indian utility. A novel algorithmic method is also presented for producing serially-complete distribution transformer loading profiles. Once the validated network models and cleaned loading profiles are available DER planning studies can be conducted. This requires implementation of DER use cases such as for BESS and EVs.

As EVs are rapidly becoming commonplace worldwide, many states in India are setting the trend by encouraging fast EV rollouts in urban areas. To assess the potential impacts of grid integration of EVs, a Python-based framework is discussed in section III of this paper which estimates aggregate EV demand profiles using the developed network models. Based on EV penetration level inputs (low, moderate, or high), this framework first determines the required number and locations of residential, workplace, and public charging infrastructure. Once the number and locations of the chargers are identified, the framework determines charging profiles under three possible scenarios: residential-dominant (mostly overnight charging), workplace-dominant (morning to afternoon), or public station-dominant (early morning, noon, and afternoon to evening). Second, the modeled EV demand profiles are added on top of existing base loads for the feeders, within the stipulated time horizon.

To ensure safe integration of EVs, system planners want to ensure that there is enough capacity to service peak loading conditions to maintain grid reliability. However, conventional planning operations deploy expensive peaker power plants such as natural gas turbines to service high demand for electricity. Current operational practices now deploy emerging technologies such as BESS for leveling peak demands. To study the impact of BESS, it is essential to determine the location and sizing of these systems as well as implement the required control algorithm.

Section IV of this paper proposes a data driven approach for recommending three distinct battery sizes for utility-scale lithium ion batteries to be integrated into the distribution network in Delhi, India. The method ingests distribution transformer loading time series data collected by the local Utility during 2018 and produces distributions of energy and power requirements which can be used for mitigating overloading conditions during summer months, when loads and the frequency of overload occurrences is highest. This section also presents the impact of BESS peak shaving control application and how it can be used to help alleviate the possible distribution transformer overloading condition with load growth and rapid adoption of EVs in the modelled distribution feeders.

Once the network models, cleaned loading profiles and DER use cases have been developed, a simulation architecture is required to integrate them together. This architecture should provide an easy to use interface and enable multiple scenarios to be simulated in parallel while storing all data in separate directories. So, section V discusses the simulation architecture developed to run time-series simulations in parallel for all the DER use cases presented in this paper. This section also presents the results obtained using this architecture which validate the effectiveness of the developed distribution planning and analysis methodology.

II. Distribution network modelling

In many instances, utilities do not have real electric models which may be used for power flow studies, rather, maintain a GIS database in order to manage network assets. A pivotal step to enable accurate characterization of feeder operations is to convert the GIS data into a format suitable for OpenDSS, an open-source power system simulation tool for distribution systems, developed by Electric Power Research Institute (EPRI), USA. GIS-based shapefiles provide visualization for the feeder topology, optimal path and engineering design of wires and towers [4], however, a critical issue with GIS-based network diagram lies with the accuracy of network segments connectivity. For example, line segments that appear to be connected in GIS visualization could be separate by a minute distance which may not be obvious to visual perception and therefore, may result in unsuitable model for power flow analysis [5].

A. Network segments creation in GIS

The distribution network segments are represented within GIS with layers (e.g., distribution transformers, circuit breakers and low tension cables), which have different numbers of features and geometry types such as polygons, line strings and points.

The QGIS software uses line strings to represent line segments in the network, some of which are polylines, making it difficult to have access to all the features of each segment. Also, these polylines, which are continuous lines with one (or more than one) line segments, are represented as a single object in QGIS. These polylines have a single source and end point coordinates which do not fully represent them and are therefore insufficient to build electrical models in power network modelling and simulation tools. To address the issue with polylines, the following procedure A is implemented in QGIS:

- Explode each line layer: This takes each line and creates a set of new lines representing segments of the original line. The new lines have a start and an end point without intermediate nodes.
- Export the geometry of the exploded layer to nodes and attribute files using the MMQGIS plugin. The resulting line segments from step 1 have nodes with source and end coordinates.

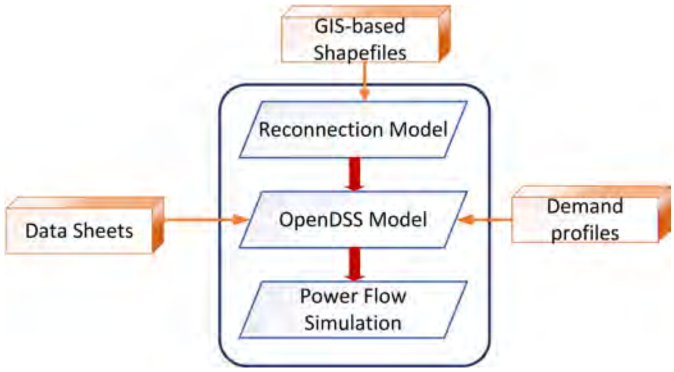


Fig. 1. GIS-based dataset translation to OpenDSS model

B. Generating OpenDSS model

This section describes the feeder reconnection process from the GIS-based shapefiles to OpenDSS format using node coordinates obtained from procedure A coupled with the corresponding attribute table to perform the following operations using python-based Networkx package:

1) Edge creation: To create edges for nodes with various line layers of the feeder such as underground (UG) and overhead (OH), the edge parameters (e.g., capacitance, positive, negative and zero sequence impedances) are defined to capture the different line characteristics.
2) Feeder head location: This is determined by identifying any particular node within the vicinity of the substation with only one neighbor connected.
3) Adding nodes and merging of neighboring nodes: Nodal elements such as the circuit breakers (CBs), DTs and switches with their properties in the attribute table for the respective feeders are combined. To determine if nodes should be merged, Euclidean distance metric is used to compute the distance between nodes.
4) Remove loops in feeder layout: For instance, circuit breaker nodes can easily form a loop which causes power flow to be trapped in a section of the network with a high tendency to increase network losses. To remove these cycles, edges connecting these nodes to create loops are removed from the network topology.

The complete procedure for translating GIS data to the OpenDSS format is illustrated in Figure 1. The reconnection models are updated with device data sheet to create the OpenDSS model, with the load profiles as inputs to the OpenDSS model.

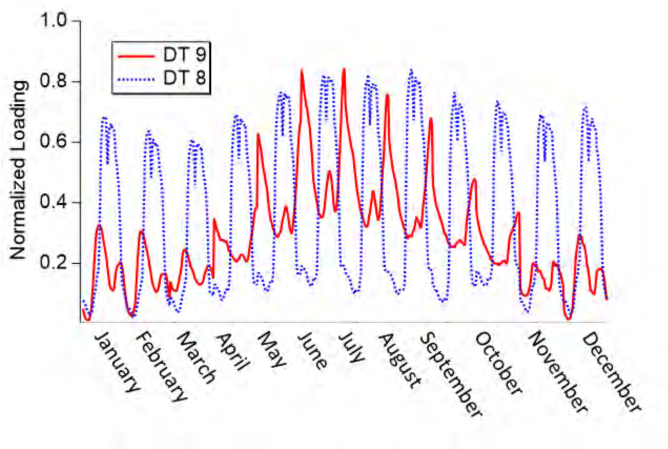


Fig. 2. Typical daily profile for each month

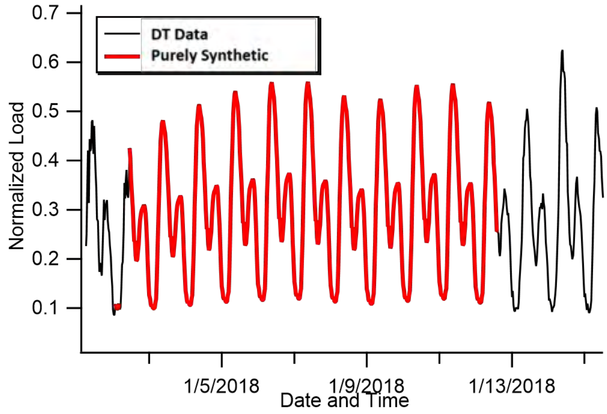


Fig. 3. Serially complete time series; corrupt data has been identified, removed, and replaced.

C. Data Cleaning

Serially complete time series distribution transformer loading data is required for quasi-static time-series simulations of the distribution feeder. Upon inspecting the distribution transformer data obtained from field measurements, it was observed that time series data sets were afflicted with several types of inconsistencies. For example, missing data and data corruption. The data cleaning process can be understood as three primary operations. The first of the primary operations is to identify and remove the afflicted data. Second, the remaining data is passed through a statistical analysis. Third and finally, a serially complete data set is compiled via an algorithm which leverages the statistical summary information.

Most of the data afflictions can be identified programmaticaly; when phases are not energized or carrying no load, when there are outages, and when data is missing entirely. The remaining rare instances during which the loading data is systematically below what is typical for a DT, are manually identified by visually inspecting the data.

After identifying and removing the problematic data, the next step in the cleaning process is to analyze the remaining data. The aim of this operation is to decouple trends within the data from the inherent variability. The typical trends are a composite of several timescales; load variability features sub hourly, hourly, diurnal, and seasonal dynamics. Here, we focus on the daily trend, which is characteristic for each month of the year, and the seasonal variability, which is characterized by a daily relative drift from the mean monthly value. To obtain the typical daily profile for each month, the mean loading condition observed during each half-hourly time point was used. This process is repeated for each month in the year, producing a profile which is used as a template or donor profile to fill missing time points as shown in figure 2. The final result for each DT represents a single serially complete time series which is normalized relative to the maximum loading condition for each transformer as shown in figure 3.

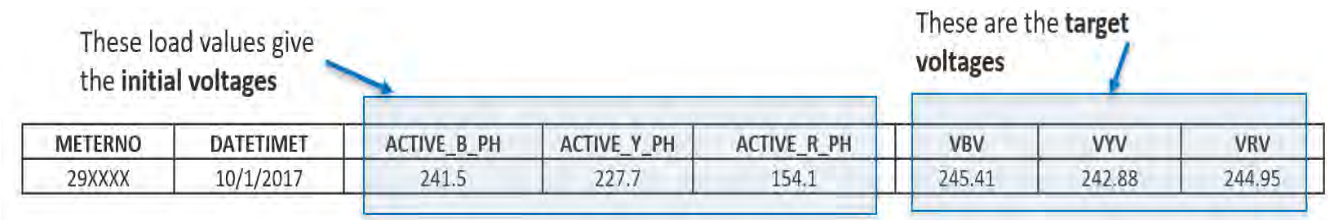
D. Load allocation

As described in the previous subsection, statistical methods had to be used to clean the metering data. Moreover, for the secondary customers only the monthly energy consumption from their billing data was available. No information was available about their power factors, peak loading or loading profiles. Thus, a new algorithm had to be created which could utilize the original profiles for the feeder head and DT data and also the monthly consumer billing data to come up with accurate customer load values.

Figure 4 shows the relevant columns available in the DT metering information. For each 30-minute interval, the per phase real and reactive powers were available and also the voltages on each phase. However, the voltage data was more consistently available than the loading information both for the DTs and feeder head. Also, since the objectives of this project involved assessing the readiness of the grid to host EVs it was essential to faithfully capture the peak loading observed on each DT [6], [7]. So, the first step was to apply the same kW values to the per phase secondary lumped loads of each DT as the peak loading values from its profile. However, since the exact capacitive compensation, if any, on each DT at the peak loading condition was not known and there were gaps in the data, the voltage drops from the feeder head to the DTs obtained from the OpenDSS models did not match the metering data (target voltages in figure 4).

To mitigate this issue, evolutionary algorithm (EA) was used to get the optimal load kW and power factor values for each phase of the DTs [8]. In this approach each DT was allocated optimal loading values separately. For the DT being optimized the load kW values were varied within $\pm 25\%$ of its peak kW values (determined from its metering data) while the PF was allowed to vary within ± 1. The other DTs were allocated the same loading values as shown in their respecting loading profiles at the peak loading time point of the DT being optimized. However, many times the other DTs had missing data and so these DTs were assumed to be loaded at 50% of their rated kVA. The tap positions for these DTs were kept at the neutral position as they did not have on-load tap changers. EA was then allowed to vary per phase load kW and power factor values until convergence was achieved. The objective function was to minimize the squared sum of deviations of the DT secondary voltages obtained from the OpenDSS models and target voltages.

Figure 5 shows the results obtained using this approach.



METERNO	DATETIMET	ACTIVE_B_PH	ACTIVE_Y_PH	ACTIVE_R_PH	VBV	VYV	VRV
29XXXX	10/1/2017	241.5	227.7	154.1	245.41	242.88	244.95

Fig. 4. DT metering information and target voltages

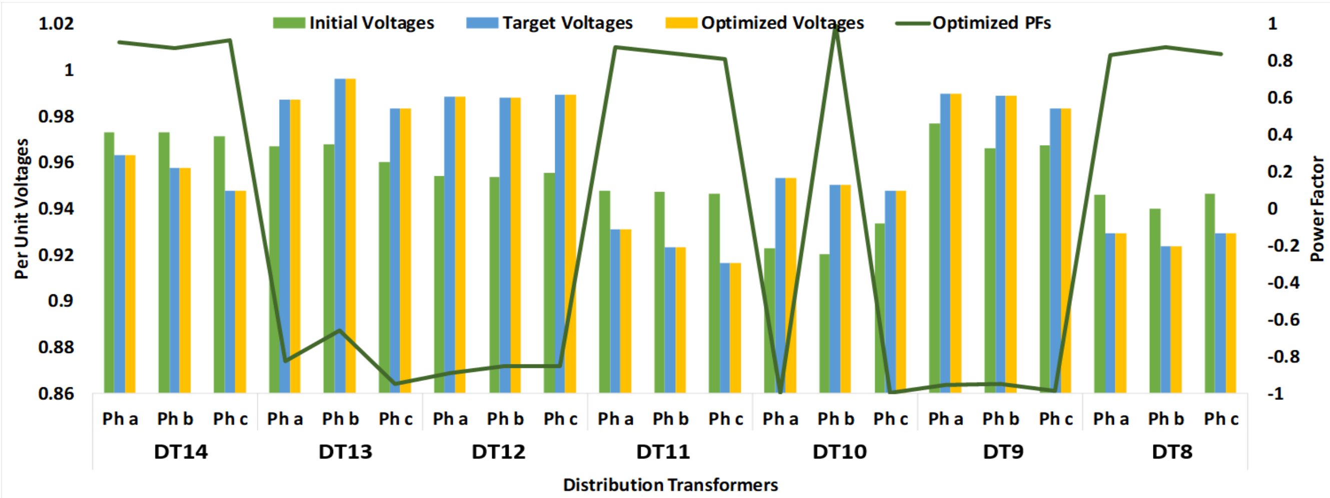


Fig. 5. Results of evolutionary algorithm without DT taps

The green bars show the voltages obtained when the kW values and power factors were directly used from the metering data. Ideally these voltages should have matched the target voltages shown as the blue bars. However, due to the reasons mentioned previously the two did not match. The yellow bars show the voltages obtained when EA achieved convergence. It can be clearly seen that the load kW and power factor values obtained from EA produce voltages which match the target voltages perfectly for all three phases. The load kW values were also very close to those observed in the metering data. However, some of these voltages could only be obtained when the power factor was negative, which indicated voltage rise due to the presence of capacitive compensation or a higher DT tap setting. So, this approach was modified and the power factors were restricted to be between [0.8,1] and the DT tap settings were allowed to vary from [0.9,1.05] in discrete steps of 0.025 to mimic the 6 available taps per DT. Using this approach most optimal voltages were closer to target voltages than the initial voltages and realistic power factors and DT tap positions could be determined.

Using the modified approach the correct per phase load kW and power factor values were obtained for all the transformers. These loading values gave the correct voltage drops from the feeder head to the DT secondaries for each DT at their respective peak loading time points and also captured the peak loading for each transformer faithfully. Now these lumped loads at the DT secondaries had to be distributed to all downstream customers. So the total number of customers per DT were divided equally in all three phases. Then the proportion of kWh consumption of each customer was calculated as a percentage of the total kWh consumption of all loads on the DT. Based on these proportions the DT lumped loads were allocated to each customer. This ensured that the total loading on each phase was exactly the same as determined by EA and each load had a kW value in proportion to its energy consumption. Figure 6 shows the per phase loads in kW allocated to secondary consumers of a DT arranged in descending orders of magnitude. Finally, since the original GIS files did not have any secondary customer nodes, new nodes were artificially created based on the plot sizes observed in the modeled area and loads were attached to these nodes as shown in figure 7.

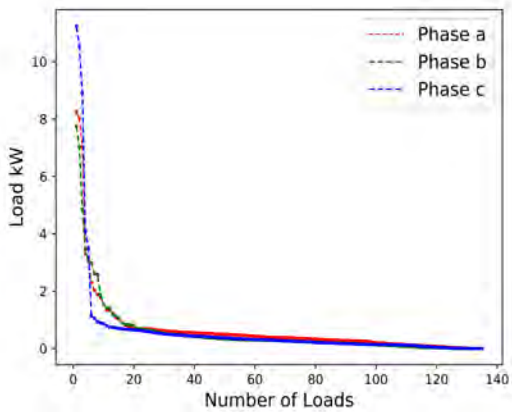


Fig. 6. Loads allocated to secondary consumers

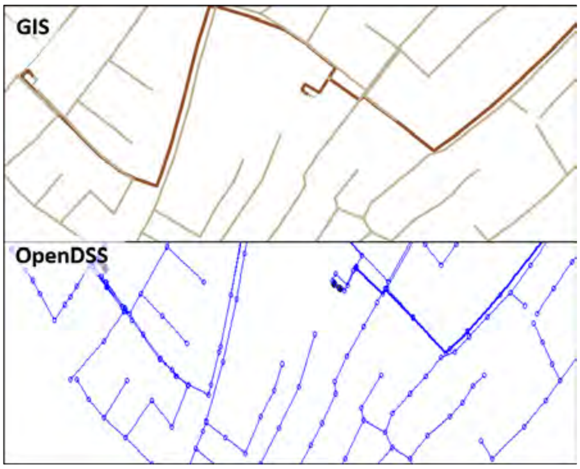


Fig. 7. New nodes created to connect secondary customers

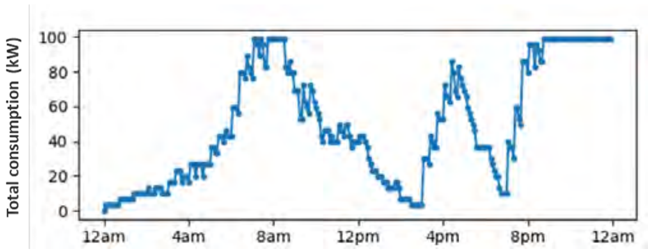


Fig. 8. Sample demand profile of a public charging station

III. EV Demand modelling

To evaluate the grid impacts, EV load was modeled as spot demand profiles for various randomized locations representing diffident scenarios. For example, a residential EV charger was modeled as an additional load on top of the base load profile but a public charging station was added as a new load for which the peak load amounts to the aggregation of the charger peak demand ratings under the station. Charging scenarios are formulated based on the types of chargers as initially specified by the utility. AC chargers (230 V, 15 A, 3.3 kW) are assumed to be the most prevalent models since this provides the most inexpensive charging options. In a residential-dominant charging scenario, single AC charger is assumed to fully charge a single vehicle overnight. These chargers will be used by consumers in public or workplace-dominant modes mostly to top-off, as the charging rates are slow. Level 1 DC chargers are assumed to be available in public or workplace/commercial stations (48/72 V, 10/15 kW).

A. Daily demand profile estimates

Preliminary examples of how a public charging station behaves throughout a day are seen in Figure 8. This station in question has 30 slow chargers with a possible net peak load of 99 kW. The model takes a bottom-up approach to build the demand profile. For example, at a given time the flock of new EV is assumed to arrive at the station with varying levels of initial SOC values. These parameters are dependent on time of the day, as seen in Figure 9. The dark blue trace in Figure 9 shows how many EVs arrive at the station at different times (nearly 250 in total, the numbers

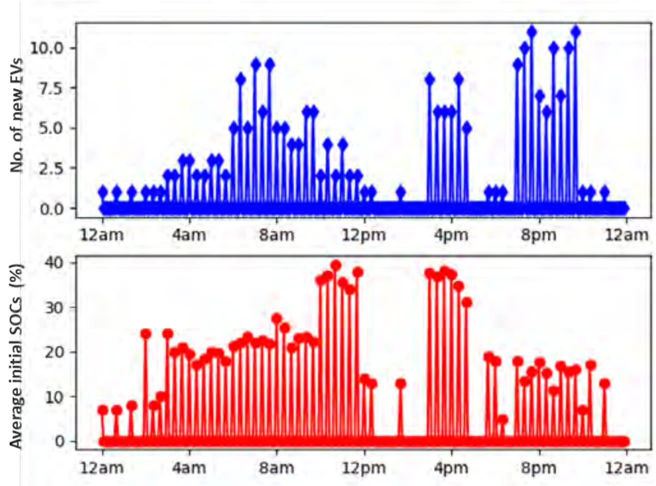


Fig. 9. Bottom-up model development for public charging station demand calculation- number of EVs and their initial SOC levels

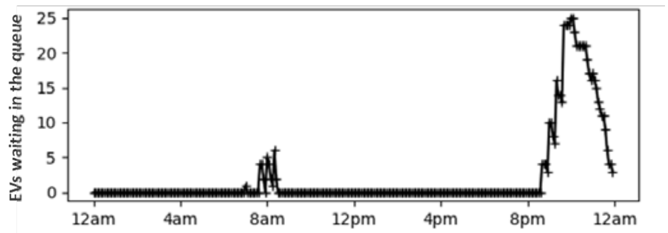


Fig. 10. Bottom-up model development for public charging station demand calculation- number of EVs waiting in the queue

are high in early morning and evening timeframe, moderate around noon time, and low at other times), and their initial SOCs are plotted by the red trace. Both variables are drawn from random distributions. Such distributions are created as a plug-n-play part of the larger model and are subject to change. Net consumption profile for this charging station thus shows constant high load in the evening through the night (Figure 8). This refers to the fact that EVs require longer time to charge in the evening as their initial SOCs are low, and consequently all the chargers in the station are occupied for this duration. The long EV queue at night is represented in Figure 10 for this example, which suggests that the waiting queue keeps growing after 8pm but tapers down around midnight.

B. Initial results

Initial results are presented in this section from the EV scenario simulation framework. There are 300 charg-

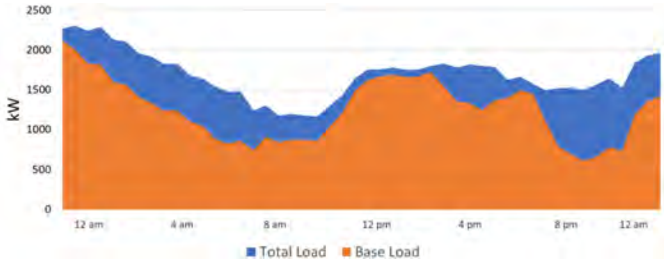


Fig. 11. Base load and total load (after EV integration) profiles for a summer day

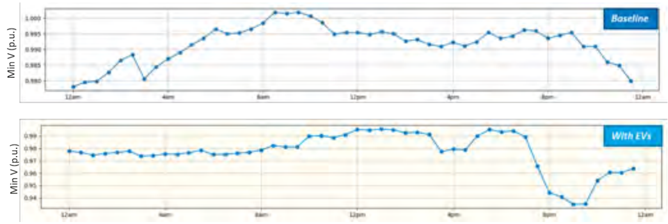


Fig. 12. Comparison of minimum voltages between baseline and EV integration scenario

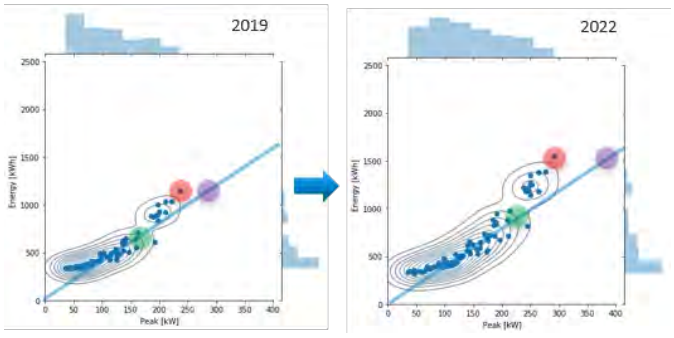


Fig. 13. Battery sizing map

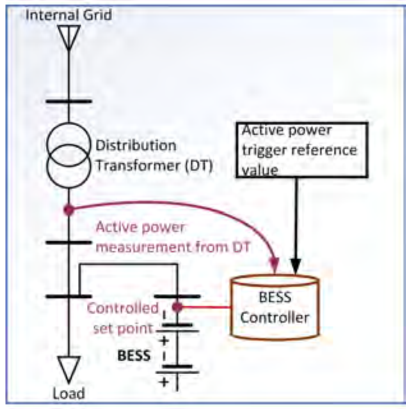


Fig. 14. Peak shaving control configuration

ers clustered among 10 charging stations (public + workplace/commercial). Number of chargers in a station may vary to reflect diversity in locations. In this scenario, there are about 2000 EVs being considered that create discrete charging events within a single day. A hot summer day profile was selected for this initial simulation. Total EV loads for all these stations and base loads for the given day are seen in Figure 11. As this figure suggests, for this scenario the EV load adds more than a MW on top of the existing base load of 1.5 MW. Voltage impacts are seen in Figure 12 which plots minimum voltages (among all the nodes) for every 30 minutes. Figure 12 shows that theres a clear voltage drop in the evening due to the high EV load as compared to the no EV or baseline scenario. Such a drop will be dependent on the daily profile, and variations in EV charging profiles.

IV. Battery Energy Storage Systems

BESS is a fast growing and reliable technique to mitigate the potential adverse impacts from integration of DERs. For instance they can charged during periods when DER generation is high but load demand is low and can be discharged during high load demand periods. This can reduce the dependence on expensive peaker plants. BESS can also be used for providing reactive power support to maintain system voltages, backup supply, energy arbitrage among others. However, before these revenue streams may be evaluated it is essential to determine the correct location and sizing of BESS as they require a significant capital investment.

A. *Battery Sizing*

This subsection describes the form of the battery sizing map which can be used to obtain the battery size appropriate for any distribution transform subject to any loading profile. Each point-pair, corresponding to every overloading instance observed during a year, can be plotted as a scatter plot. The bivariate distribution of the overloading point-pairs can be superimposed over the scatter plot as shown in figure 13. There will exist one overloading instance point-pair with the maximum power requirement. It is assumed that commercially available batteries are generally available with a 4:1 ratio between energy and power, e.g. a 2kW, 8kWh battery could be readily procured whereas a 2kW, 20kWh is not expected to be commercially available. Thus, all of the battery sizes which are recommended in this study will be on the 4:1 energy to power ratio line. There are three points which are of interest in the battery sizing map, these are (1) the peak power overloading instance point-pair shown in red, (2) the projected peak power point-pair to the 4:1 ratio line shown in purple, and (3) the 70th percentile point-pair. The 70th percentile point represents the point on the 4:1 ratio line most near the point simultaneously at the 70th percentile of power and energy for all observed overloading instances.

B. *Peak shaving control application*

Power system planning operations ensure that there is enough capacity to service peak loading conditions to maintain grid reliability. Traditionally, peaking power plants such as natural gas turbines have been used to service high demand for electricity. The peak shaving mode requires the service operator to provide trigger values for peak shaving and base loading. The BESS will discharge power into the grid if the active power demand at the measured point, DT in this case, is greater than the peak shaving upper reference limit as shown in Figure 14 .

Conversely, the BESS will charge if the load consumption at the measured point is lower than the base loading limit. This BESS control application is used to defer large investments required for system upgrade and to mitigate use of peaking generators for flattening the load profile. This research will provide insight into the impact of such BESS application on capacity deferrals.

C. *Results*

The implementation of peak shaving algorithm in 30-minute time step for one day is presented. Figure 15 shows the active power at this particular distribution transformer, SOCs of the attached local BESS and the batteries active power output with and without (base case) the peak shaving grid support.

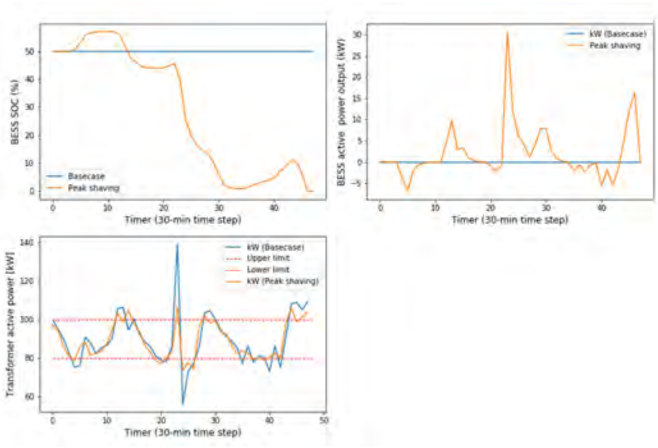


Fig. 15. Energy storage integration results at a distribution transformer for Feeder 1

This BESS control application functions such that the BESS charges during the base loading condition of the distribution transformer to prevent an exacerbation of its loading during a possible peak demand and low SOC scenario. The peak shaving algorithm discharges the BESS power to service peak demands when the upper limit threshold of the distribution transformer is violated. The BESS idles during periods when neither reference set points, upper and lower limits, are violated. The peak shaving control application continues to function until the BESS is completely depleted.

V. Simulation Architecture

In order to assess the grid readiness of the modeled network to host EVs, a large number of time series simulations had to be completed. For instance the baseline had to be simulated over 10 years at 30-minute resolution to determine required network upgrades. The selected upgrades would then have to be modeled to verify that they can indeed correct the observed violations. Along with the baseline simulations a number of EV scenarios have to simulated followed by BESS use cases. Simulating them serially on a local machine would be time intensive and inflexible. Thus, a simulation architecture had to be created which could run all of these simulations in parallel by leveraging the high performance computing facilities available at NREL.

Figure 16 shows the architecture created for this purpose. A command line interface was developed which can be used to specify the names of all the feeders to be simulated, the time resolution required, total simulation time and all the EV and BESS use cases. These inputs are then sent to a job handler which arranges them in batches and each batch is sent to a task node. On each node the batch is split into individual time series simulations which are run in parallel on the different cores. The raw data is stored in separate directories which is then post processed to get the grid readiness metrics.

To get the baseline results, time series simulations were run on the developed network model for the entire year using time series profiles developed using the statistical methods described in the previous sections. It was essential to ensure that the DTs were actually observing the same loading throughout the year as expected from the allocated loads. So, the loading observed on each DT at all time points was stored in a data structure and exported as an output file. This year-long baseline loading profile was then compared with the expected loading of each DT. Expected loading is the sum of loading on each phase of the DT at each time point, obtained by multiplying the load allocated using EA with the time series profile multiplier, $DTload^{EA}_{perphase} * Load_{mult}$. As can be seen in figure 17, the actual loading is slightly higher than the expected loading because of the losses which verified that the network model and OpenDSS simulations were giving correct results.

The original DT meter data and OpenDSS outputs were also compared. These comparisons could only be made for a subset of DTs which had relatively fewer gaps in the data as shown in figure 18. Even though the OpenDSS output includes the impact of the EA based load allocation algorithm and the statistical methods used for filling in missing or bad data, it looks very similar to the raw input data. This helps in validating the effectiveness of the simulation platform described in this paper to conduct meaningful distribution planning analysis using data sources readily available with the Indian utility companies.

VI. Future Work

Time series simulations can provide a lot of valuable information. For each one of the multi-year time series simulations a suit of grid readiness metrics will be evaluated. These metrics will provide information about the required network upgrades to mitigate thermal and voltage violations. The EV demand profiles will also be included to simulate the network impacts of varying levels of EV penetration. The BESS use cases such as peak shaving will then be implemented along with the EV scenarios to determine the effectiveness of BESS in facilitating EV integration.

VII. Conclusions

This paper presented a platform developed to conduct detailed distribution planning and analysis studies. This platform uses input data in the same format as is readily available with the utility and then processes it to a usable format. This platform can be used to model a detailed distribution network model including both the primary and secondary networks, and get accurate load allocations and statistically correct loading profiles.

The modular nature of this platform allows it to be easily extended to any DER use case in addition to the BESS and EV use cases already implemented. The simulation architecture is also flexible enough to run a multi-year time series analysis with these use cases and evaluate the grid readiness metrics. The presented baseline results validate the effectiveness of this platform to generate accurate models and power flow results.

Acknowledgment

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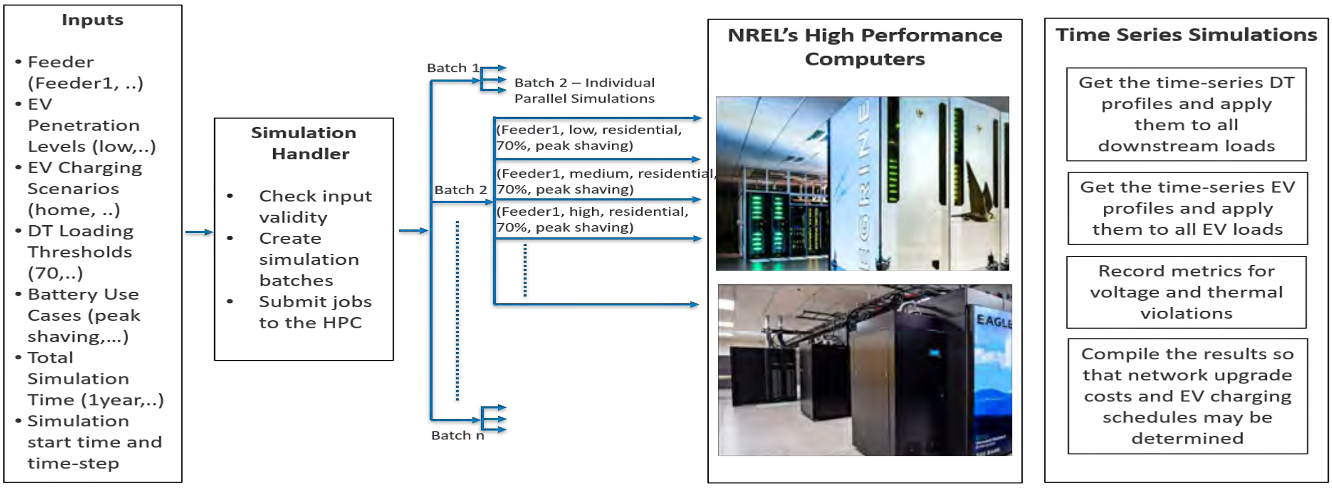

Fig. 16. Simulation architecture used to run hundreds of time-series simulations in parallel

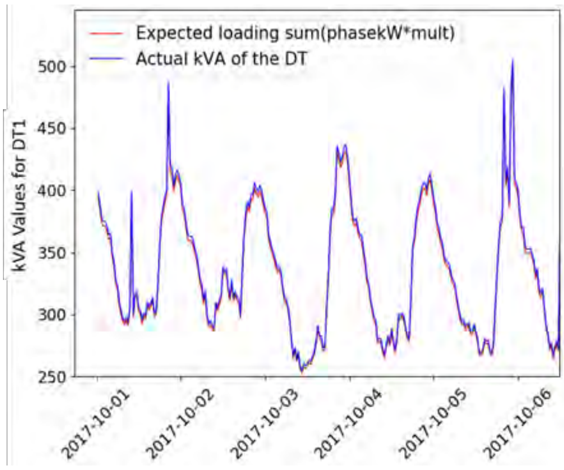

Fig. 17. Expected vs actual DT loading

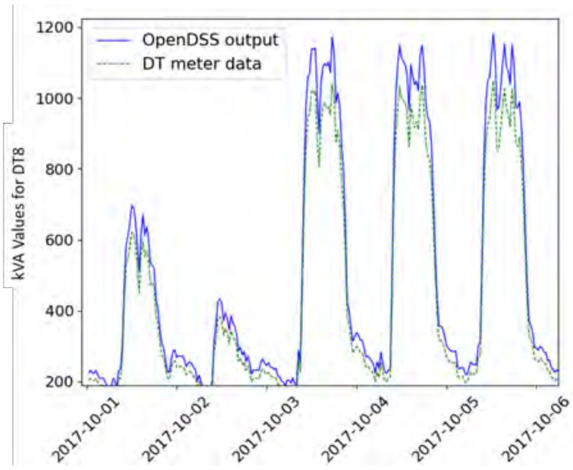

Fig. 18. DT Meter data vs OpenDSS outputs

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