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# IMPROVED LOAD MODELLING FOR EMERGING DISTRIBUTION SYSTEM ASSESSMENTS

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## Abstract

Distribution system modelling and analysis with growing penetration of DER requires more detailed and accurate distribution load modelling. Smart meters, DER monitors, and other distribution system sensors provide a new level of visibility to distribution system loads and DERs. However, there is a limited understanding of how to efficiently leverage the new information in distribution system load modelling. This paper presents the assessment of 11 methods to leverage the emerging information for improved distribution system active and reactive power load modelling. The accuracy of these load modelling methods is assessed both at the primary and the secondary distribution levels by analysing over 2.7 billion datapoints of results of feeder node voltages and element phase currents obtained by performing annual quasi-static time series (QSTS) simulations on EPRI's Ckt5 feeder model.

## 1 Introduction

Accurate modelling of loads is fundamental for distribution system modelling and many applications in distribution operations and planning [1]. In particular, accurate load modelling is important for DER hosting capacity studies and system expansion planning. In static load modelling, loads can be represented by their active and reactive power information. With the advent of advanced metering infrastructure (AMI), load information could be recorded at a desired resolution, and loads could be represented with their historical data. However, this process requires cleaning and processing large data sets, without a clear understanding of the accuracy gained in doing so. Moreover, many utilities have still not deployed AMI, and many existing AMI systems do not provide reactive power measurements. In general, there is a limited understanding in how to efficiently utilize the new level of visibility provided by AMI to reach an appropriate trade-off between model accuracy and effort [2].

Alternatively, loads can be represented using fewer data sources, such as substation SCADA, but with reduced spatial or temporal granularity. Conventionally, loads have been represented with load allocation, where a known feeder head demand is allocated to individual loads based on their energy consumption (kWh) or based on the rating of the service transformer that supplies them [1], [3]. However, this traditional load modelling provides limited spatial and temporal detail [1], [4].

Prior research has investigated the value of improved spatial and temporal active power information. Spatially, the application of load's historical information such as load kWh or load classes instead of transformers kVA ratings was investigated in [1], [3], [4], [5], [6], [7]. References [1], [4], and [7] has shown that, from commonly used load allocation methods, the best temporal load modelling accuracy is achieved with monthly kWh allocation. The value of utilizing SCADA measurement captured at multiple geographical locations to increase grid visibility and load model accuracy was also investigated in [1]. However, the reactive power modelling was simplified, and the value of increased load allocation frequency was not investigated.

This paper shows the analysis of 11 methods to leverage the emerging information for improved distribution system active and reactive power load modelling. The analysed methods represent a range of approaches to leverage different levels of visibility to distribution feeder load conditions. Annual quasi-static time series (QSTS) simulations are performed with OpenDSS [8] to quantify the accuracy of the different load modelling methods in presenting the thermal loading and nodal voltages. Additionally, the accuracy of the load modelling methods was evaluated separately for primary and secondary distribution circuit levels. The secondary circuit accuracy evaluation provides fundamental insights for emerging applications including studies of smart inverter functions [9], and adaptation of demand response [10].



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## 2 Methodology

The overall approach of this study consists of two steps. In the first step, QSTS simulation with the reference active and reactive power AMI data set was performed to obtain emulated measurements that were assumed to be available according to the spatial and temporal granularity of each load modelling method. In the second step, these emulated measurements were utilized to model the loads according to the methodology of each modelling method of interest. The accuracy of the load modelling methods was then assessed by evaluating the differences in voltages and element thermal loading between their QSTS results and the QSTS results of the reference data set.

*2.1 Case Study Distribution Circuit Model*

The accuracy of different load modelling methods was analysed on the EPRI's "Ckt5" feeder model that is distributed with the OpenDSS software [8]. Ckt5 is a model of a 5-km long real U.S. 12.47 kV distribution feeder that supplies 1,379 residential loads through 591 MV/LV service transformers. To facilitate easier comparison of the analysed load modelling methods, controllers for switched-capacitor banks were disabled. The circuit model has no voltage regulators, or load tap changer (LTC). In the Reference case, all loads were directly modelled with AMI active and reactive power measurements with 15-min resolution obtained from a U.S. utility. After integrating the Reference case AMI data, the ratings of some service transformers and service lines were increased to avoid threshold violations.

*2.2 Load Modelling Methods*

Table 1**Error! Reference source not found.** summarizes the 11 load modelling methods in four research areas that were analysed to investigate the value of alternative spatial and temporal information.

*2.2.1 Common Load Modelling Practice*: The first load modelling method, referred as business-as-usual (Case BAU), represents a load allocation practice commonly applied by North American distribution utilities. With this method, load allocation was performed for the feeder peak load and all loads were uniformly scaled for other time instances based on the feeder head load active power load profile. Results from this method were used to benchmark the potential improvement provided by other improved modelling methods.

*2.2.2 Value of Load Allocation Frequency:* Performing load allocation more frequently may offer better representation of the spatial-temporal diversity of the feeder loads. This research area investigated the value of increasing the load allocation frequency from a single (peak load) time instance (case BAU) to monthly peak load time instances (case Monthly), and to every time instance (case Time-wise).

*2.2.3 Value of Feeder Sensors:* Conventional load modelling methods are based on limited visibility [1], [4], where the individual load consumption is traditionally assumed to follow the shape of the load at the feeder head. This research area assessed the value of the visibility provided by a single feeder head sensor (case BAU), three added feeder sensors (case BAU_S), service transformer measurements (case BAU_TS), and AMI active power (but not reactive power) data from every load (case Ref_PAMI).

*2.2.4 Value of Reactive Power Information:* The load modelling methods discussed above modelled the reactive power consumption of loads based on system-wide annual average power factor (PF). This research area investigated the value of additional detail in reactive power modelling. To analyse the value of AMI reactive power measurements, a modified version of the Reference case was created by assuming a full observability of active power from AMI but where the reactive power of loads was modelled based on a constant single feeder-wide power factor (case Ref_PAMI). To analyse the value of temporal feeder-level reactive power measurements, a modified version of Case BAU was created by adjusting all loads to follow the feeder PF at every time step (case BAU_FPF). The value of spatial load-specific reactive power information was analysed with cases BAU_CYPF and Monthly_CYPF. Finally, the value of both improved spatial and temporal reactive power information was analysed with load-specific monthly average (case Monthly_CMPF).

Table 1 The 11 analysed load modelling methods with high, medium, and low detail shown in green, yellow, and white shading, respectively.

| Case Abbreviation | Load Active Power Measurement | | Load Reactive Power Measurement | | SCADA (P & I) Visibility Level | Load Allocation Frequency |
|---|---|---|---|---|---|---|
| | Resolution (Temporal Info) | Type (Spatial Info) | Resolution (Temporal Info) | Type (Spatial Info) | | |
| Reference | 15-minute kW | Load-specific kW | 15-minute kvar | Load-specific kvar | N/A | N/A |
| BAU | Peak month kWh | Load-specific kWh | Yearly average PF | System-wide average PF | Feederhead | Peak month |
| Monthly | Monthly kWh | Load-specific kWh | Yearly average PF | System-wide average PF | Feederhead | Month |
| Time-wise | Monthly kWh | Load-specific kWh | Yearly average PF | System-wide average PF | Feederhead | 15 Min |
| BAU_S | Peak month kWh | Load-specific kWh | Yearly average PF | System-wide average PF | Feederhead & 3 feeder sensors | Peak month |
| BAU_TS | Peak month kWh | Load-specific kWh | Yearly average PF | System-wide average PF | Transformers | Peak month |
| Ref_PAMI | 15-minute kW | Load-specific kW | Yearly average PF | System-wide average PF | N/A | N/A |
| BAU_FPF | Peak month kWh | Load-specific kWh | 15-minute kvar | Feederhead kvar | Feederhead | Peak month |
| BAU_CYPF | Peak month kWh | Load-specific kWh | Yearly average PF | Load-specific PF | Feederhead | Peak month |
| Monthly_CMPF | Monthly kWh | Load-specific kWh | Monthly average PF | Load-specific PF | Feederhead | Month |
| Monthly_CYPF | Monthly kWh | Load-specific kWh | Yearly average PF | Load-specific PF | Feederhead | Month |

## 3 Results

The results for nodal voltages and element thermal loadings were grouped according to different levels of interest. Nodal voltages were grouped into three categories: V_MV, V_LV1 and V_LV2. The first category (V_MV) is the analysis of the medium-voltage level of the distribution system that conventionally has been the focus of feeder-wide studies. The remaining categories (V_LV1 and V_LV2) are the service transformer secondary, and customer interconnection points, respectively. Three equipment categories were considered for thermal loading analysis: medium-voltage level lines (L_MV), low-voltage level service lines (L_LV), and MV/LV service transformers (Xfmr).

As follows, the accuracy of the analysed load modelling methods is quantified based on the accuracy of the lowest voltage conditions and the highest thermal loadings, two metrics that are of key interest for distribution planners. The accuracy of the other load modelling methods was summarized as the average (over all nodes and elements) difference/error (of the minimum voltages and maximum loadings) against the Reference case.

### *3.2 Accuracy of Common Load Modelling Practice*

Table 2 shows the average error (over nodes and elements) of the yearly minimum node voltages and maximum element loadings against the Reference case.

Table 2 Average errors for the BAU case

| Elements | | Error against reference |
|---|---|---|
| Min | V_mv [pu] | +0.0025 |
| | V_lv1 [pu] | +0.0048 |
| | V_lv2 [pu] | +0.0062 |
| Max | L_mv [%] | -0.73 |
| | L_lv [%] | -14.28 |
| | Xfmr [%] | -26.98 |

As shown in Table 3, BAU captured the nodal voltages and thermal loading at the primary distribution level (V_MV and L_MV) with a reasonable accuracy but quite inaccurately at the low-voltage secondary circuit level. On average, BAU overestimated the minimum load voltages by 0.006 pu, which is equivalent to 12% of ANSI C84.1 service voltage range A (±0.05pu). Note that this is the average (over all loads) and the minimum voltage of some loads was considerably more underestimated. BAU also underestimated, on average, the maximum service transformer loading by 27% (and much more for some service transformers). To summarize, BAU was found to be satisfactorily accurate at the MV level but unable to capture the extreme conditions at the secondary circuit level.

### *3.3 Value of Load Allocation Frequency*

Table 4 compares the errors for the three load allocation frequency cases. As shown in Table 4, increased load allocation frequency slightly improved the accuracy of load modelling when compared with BAU. This improvement was more noticeable in the low-voltage secondary circuits than at the medium-voltage level. For instance, the average accuracy improvement for minimum LV2 nodal voltage and maximum Xfmr thermal loading was 0.0007 pu (1.5%) for time-wise allocation, and 0.0002 pu (1.2%) with monthly allocation. In this study, worst-case conditions for voltage and thermal loading were found during the peak load month, and since the other two alternative methods have similar load models during the peak month, the accuracy of these methods was not significantly improved. The differences could be more noticeable for other metrics not analysed here.

Table 4 Average errors for load allocation frequency cases

| Elements | | BAU | Monthly | Time-wise |
|---|---|---|---|---|
| Min | V_mv [pu] | +0.0025 | +0.0025 | +0.0019 |
| | V_lv1 [pu] | +0.0048 | +0.0047 | +0.0040 |
| | V_lv2 [pu] | +0.0062 | +0.0060 | +0.0053 |
| Max | L_mv [%] | -0.73 | -0.70 | -0.61 |
| | L_lv [%] | -14.28 | -13.62 | -13.50 |
| | Xfmr [%] | -26.98 | -25.80 | -25.42 |

### *3.4 Value of Feeder Sensors*

Table 5 compares the results for the cases with different feeder sensors. The results indicate that the increased grid active power visibility can improve load modelling accuracy. Sensors at the transformer or customer level noticeably improved the accuracy of the simulated secondary circuit voltages, and service transformer and line loadings. In BAU_TS, some errors can be observed in the L_LV lines as BAU_TS did not represent load diversity downstream of the service transformers. Ref_PAMI was the most accurate method when reactive power information is not available.

Table 5 Average errors for feeder sensor cases

| Elements | | BAU | BAU_S | BAU_TS | Ref_PAMI |
|---|---|---|---|---|---|
| Min | V_mv [pu] | +0.0025 | +0.0024 | +0.0022 | +0.0022 |
| | V_lv1 [pu] | +0.0048 | +0.0047 | +0.0023 | +0.0023 |
| | V_lv2 [pu] | +0.0062 | +0.0059 | +0.0026 | +0.0024 |
| Max | L_mv [%] | -0.73 | -0.62 | -0.09 | -0.08 |
| | L_lv [%] | -14.28 | -14.16 | -6.98 | +0.25 |
| | Xfmr [%] | -26.98 | -26.56 | -0.06 | +0.19 |

### *3.5 Value of Reactive Power Information*

Table 6 compares the results for the cases with different reactive power modelling approaches. As Table 6 shows, additional spatial and temporal reactive power information provided little accuracy improvement for thermal loading. However, the accuracy of nodal voltages was sensitive to the choice of spatial and temporal reactive power information. Spatially, the reactive power at a single location may not be a good representation of the reactive power for all locations (BAU_FPF). Temporally, utilizing annual average of the loads' PF (BAU_CYPF and Monthly_CYPF) resulted in a less accurate load model as compared to BAU. On the other hand, monthly average load-specific PF (Monthly_CMPF) provided a noticeable accuracy improvement for the overall nodal voltages.

Table 6 Average errors for reactive power cases

| Elements | | BAU | BAU_FPF | BAU_CYPF | Monthly_CYPF | Monthly_CMPF |
|---|---|---|---|---|---|---|
| Min | V_mv [pu] | +0.0025 | -0.0040 | +0.0036 | +0.0036 | +0.0001 |
| | V_lv1 [pu] | +0.0048 | -0.0025 | +0.0060 | +0.0058 | +0.0021 |
| | V_lv2 [pu] | +0.0062 | -0.0013 | +0.0073 | +0.0071 | +0.0033 |
| Max | L_mv [%] | -0.73 | -0.46 | -0.73 | -0.70 | -0.70 |
| | L_lv [%] | -14.28 | -13.99 | -14.23 | -13.57 | -13.56 |
| | Xfmr [%] | -26.98 | -25.98 | -26.92 | -25.72 | -25.70 |

## 4 Conclusion

This paper analysed the value of improved spatial and temporal active and reactive power information for distribution system load power modelling. A reference was obtained from QSTS results with full visibility to the active and reactive power of all loads. Nine improved methods were benchmarked against a load modelling practice commonly applied by North American distribution utilities. The key findings include:

- The load modelling method conventionally applied by North American utilities (BAU) resulted in satisfactory results at the primary distribution level. However, voltage and thermal loading results were not accurate at the secondary distribution level. On average, the annual minimum load voltages were overestimated by 12% of ANSI C84.1 service voltage range A (±0.05pu), and the annual thermal element loading was underestimated by 27%.
- Increasing the load allocation frequency from annually (BAU) to monthly (Monthly), and to time-wise (Time-wise) yielded limited benefits for the analysed case study since the annual peak load already captured some of the most extreme conditions. This may not generally apply under different feeder load conditions, or other metrics not analysed in this paper.
- Load modelling accuracy increased as grid visibility level was increased from feeder head level (BAU), to feeder sensors (BAU_S), to service transformer level (BAU_TS), and to load level (Ref_PAMI).
- From the analysed cases, load modelling with utilizing active power AMI with system-wide PF (Ref_PAMI) showed the best load modelling accuracy at both primary and secondary distribution levels.
- Improved spatial and temporal reactive power information provides small accuracy improvement for the thermal loading. However, monthly average load-specific PF (Monthly_CMPF) showed the best overall nodal voltage accuracy without a full integration of AMI data into the model.

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