REINFORCEMENT OF ELECTRIC NETWORKS TO ENHANCE THE ADOPTION OF ELECTRIC VEHICLES: AN UNCERTAINTY-BASED CONDUCTOR RESIZING APPROACH

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ABSTRACT

This paper demonstrates the application of an uncertainty-based conductor resizing approach in reinforcing low voltage electricity networks with high penetration of electric vehicles (EVs). The approach applies a three-step uncertainty-based procedure to determine the technical performance of the existing networks under varying EV penetration scenarios. Risk-based performance of individual network elements (i.e., nodes and conductor branches) are assessed to provide insight into the locations with potential congestion and power quality issues, thereby allowing the planning for appropriate reinforcement strategies. A simplified case study illustrates the approach's efficacy in improving feeder hosting capacity to EVs by resizing conductors.

INTRODUCTION

Global transition towards sustainable and renewable energy sources has led to increased adoption of technologies such as solar photovoltaics (PV), battery energy storage, and electric mobility (e-mobility) systems such as electric vehicles (EVs) [1]. The adoption of EVs presents an opportunity to reduce the global carbon footprint attributed to the transport sector [2]. However, high penetration and uncoordinated connection of EVs on low voltage (LV) networks are associated with various technical challenges, mainly violation of voltage drop, voltage unbalance, and thermal loading conditions of conductors and transformers [3]. Furthermore, the uncertainties characterizing EV location and charge power requirements, termed allocation, and the EV time of use (ToU) patterns increase the operational challenges facing distribution network planners. To address these challenges and at the same time promote increased EV adoption, distribution system operators need to understand the EV energy requirements, assess the capability of the existing infrastructure to host such systems, termed hosting capacity (HC), scope the reinforcement needs for HC enhancement strategies, and possibly develop new design principles for new electrification projects involving these EV systems [4].

Increased adoption of EVs on distribution networks requires comprehensive LV network planning considering a myriad of factors. Detailed modeling of the mobility characteristics (distance traveled and transit parameters), the corresponding location- and time-specific battery state of charge (SoC), and vehicle energy requirements (EV ToU and charging location) are critical for comprehensive grid impacts assessments that lead to reliable HC conclusions [2], [5]. The topic of HC evaluations has received a lot of attention, and the combination of stochastic and probabilistic approaches is widely acknowledged as the state-of-the-art in HC assessments [2] From these studies, the HC results indicate stringent limits to accommodating EVs. This can be attributed to the increased network load, particularly when coincident with the system peaks, and the uncertainty characterizing EV ToU and SoC patterns, which disrupt the predictability of the network's load profile and operations [6]. In that light, the existing networks are not optimized for the technical and operational needs arising from EV adoption. As a result, network reinforcement and upgrades are required to enhance existing networks' HC to EVs. This focus area is still evolving and receiving more attention as EV penetration grows.

Network planning for a high share of EVs centres mainly on four aspects: (1) modeling future EV loading scenarios, (2) HC assessment for the existing networks under the future scenarios, (3) identifying areas requiring reinforcement, and (4) design and implementation of reinforcement strategies. Previous studies have also proposed the use of demand-side management (DSM) and other EV management strategies. In [2], the authors propose EV management to increase the feeder HC. Similarly in [6], the authors investigated the impact of increased EV adoption on distribution upgrades and proposed the use of DSM and storage to increase the feeder HC. While the reported studies acknowledge relevant aspects in EV modeling, uncertainty factors such as allocation and ToU are not comprehensively considered. Future-oriented planning requires accurate models which incorporate EV uncertainties and allow for the analysis of the performance of each feeder element. For existing networks, uncertainty-based reinforcement of the primary network components (feeder conductors and transformers) could be a necessary optimal reinforcement strategy.

This paper provides a comprehensive probabilistic approach to HC enhancement of LV feeders with EVs, based on conductor resizing. The approach considers input uncertainties relating to household and EV loads, including EV ownership (or charging location) and EV penetration, by simulation using a combined stochastic-probabilistic framework. As a modified approach to standard HC assessments, the presented approach focuses on individual feeder elements' technical performance under probabilistic-generated future scenarios. It, therefore, provides granular information relating to the sections that need voltage support and congestion relief as the EV penetration increases. Probabilistic results afford the application of risk-based output analysis to achieve reliable reinforcement solutions. In this paper, conductor resizing is demonstrated as a network reinforcement and HC enhancing strategy.

METHODOLOGY

Figure 1 illustrates the flow chart of the methodology. A three-step probabilistic approach with an "input-process-output" algorithm reported in [7] is adopted. At the input stage, statistical load modeling is applied to characterize the uncertainty of household loads and EV charging demand in 5-minute periods. The probabilistic models supplemented by the feeder model constitute the inputs to the process stage where a grid impact study is conducted based on a probabilistic load flow analysis (PLF) with simulated scenarios from a Monte-Carlo simulation (MCS) process. Assessment of the bus voltage and thermal loading conditions in the 'Feeder Compliance Testing' segment inform resizing measures implemented in the 'Risk-based Conductor Reinforcement' segment. The process is repeated according to set stop-criteria. The sections that follow discuss the methodology components in more detail.

Input stage: Stochastic input modeling

The inputs at this stage are the customer load model and

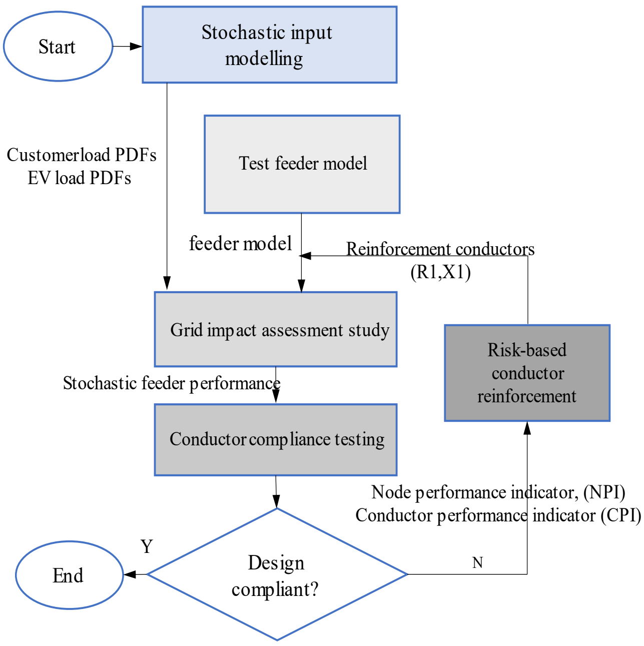

Figure 1: Flow chart of the proposed methodology

the EV load model. Beta PDFs are used to characterize the customer load at a time of peak demand for the winter season. The variability in the customer and EV load is characterized at specified time intervals coinciding with a time of maximum load using beta PDF. The use of beta distribution is motivated by the versatility of the distribution and its ability to take different shapes as dictated by the shape parameters, alpha, α, and beta, β derived using equations 1 and 2.

$$\alpha = \left({}^{1-\mu}/_{\sigma^2} - {}^{1}/_{\mu}\right)\mu^2 \tag{1}$$

$$\beta = \alpha\left({}^{1}/_{\mu} - 1\right) \tag{2}$$

σ and μ are the standard deviations and the mean of the load data.

In this study 1000, load and EV load profiles are used in the generation of statistical models. The beta PDF parameters of the derived load models form the inputs to the PLF analysis. The selected time interval in the model represents the coincident interval for household and EV loads. This is assumed to occur at 7 pm in winter.

Grid impact assessment

A grid impact assessment and conductor performance validation analysis are carried out at this stage. These processes test the adequacy of the network to support a given EV penetration. To do this, three concurrent processes namely: (1) the stochastic simulation of EV load scenarios; charging location on feeder node and power demand, (2) the PLF analysis of generated scenarios, and (3) conductor compliance validation based on voltage drop and conductor loading constraints. This is implemented as a nested simulation of the PLF computation embedded in a stochastic MCS allocation simulator.

Stochastic EV allocation simulation

EV allocation is simulated using an MCS approach with 1000 allocation scenarios at each EV penetration level for a set range in steps of 1 EV at a time. The selection of 1000 is deemed sufficient based on similar studies conducted in [8]. An MCS scenario involves the random selection of a charging location (to node and phase) and a charging load from probabilistic models developed in the input stage.

Probabilistic load flow analysis and compliance testing

For each generated EV load scenario, a PLF analysis based on the Herman-Beta extended (HBE) transform is conducted to evaluate technical feeder performance under EV penetration scenarios. The HBE transform was developed in [9] and extended in [10] to include MCS for PLF analysis and is used in power flow analysis for passive and active radial distribution feeders. The HBE-PLF analysis informs feeder compliance in selected time intervals according to voltage-drop and conductor loading constraints. This analysis is performed for individual nodes and branches. The load flow results out of the HBE, like its inputs, are characterized as beta PDFs and analyzed at a 2.5% risk in line with the local design principles. The risk-adjusted voltage and thermal loading values are recorded for each MCS EV allocation scenario and tested penetration level. As a result, scatterplots of voltage and loading impacts can be plotted for each node and branch, representing the range of component performance under EV allocation scenarios. To determine the loadability or HC of the individual components, a further risk-based nodal and branch performance analysis is conducted considering a further 2.5 % risk. This analysis achieves a single feeder voltage drop, $\mathrm{VD_P}$, and conductor loading, $\mathrm{CL_P}$, performance index for each feeder branch and node, for the whole penetration range, $0 < p < p_{max}$. The cascaded risk amounts to 5% risk: 2.5% risk integrated into the PLF results and 2.5% risk considered in the nodal and branch performance indices. The derivation of these indices is given in equations (3) and (4).

$$\mathrm{CL_{P\_risk}} = \mathrm{prctl}(\mathrm{CL_P}, 97.5); \forall \text{ branches}, \mathrm{B} \quad (3)$$
$$\mathrm{VD_{P\_risk}} = \mathrm{prctl}(\mathrm{VD_P}, 2.5); \forall \text{ nodes}, \mathrm{N} \quad (4)$$

$\mathrm{VD_{P\_risk}}$, $\mathrm{CL_{P\_risk}}$ are the risk-adjusted voltage drop and loading performance for all branches and nodes on the feeder and are considered together with the performance constraints, to form the basis of selecting the reinforcement conductors. The symbol prctl stands for the percentile.

Output: Risk-based conductor reinforcement

Node performance index (NPI) and conductor performance index (CPI) are calculated based on equations (3) and (4) and recorded for each branch and node.

$$\mathrm{NPI} = \mathrm{VD_{P\_risk}}/\mathrm{VD_{limit}}; \ \forall \text{ Nodes}, \mathrm{N} \quad (5)$$
$$\mathrm{CPI} = \mathrm{CL_{P\_risk}}/\mathrm{CL_{limit}}; \ \forall \text{ branches}, \mathrm{B} \quad (6)$$

$\mathrm{VD_{limit}}$, $\mathrm{CL_{limit}}$ are the voltage drop and conductor loading per unit limits and are set at 0.9 and 1 pu. For non-compliance, the CPI and NPI indices are lesser and higher than 1 respectively indicating voltage or loading violation. In instances with voltage or loading violations, an iterative resizing approach is conducted to adjust the noncompliant feeders. Short-line feeders with a low X/R ratio are assumed to be purely resistive, and the replacement is carried out by scaling down the initial per-km resistance, R_0 based on the following set of equations.

$$\mathrm{R_{V\_new}} = \mathrm{R_0} \text{ x NPI} \quad (7)$$
$$\mathrm{R_{CL\_new}} = \mathrm{R_0}/\mathrm{CPI} \quad (8)$$

The feeder model is then updated, and the grid impact assessment is conducted with the new resistances until the compliance condition is achieved. The conductors with the closest R values are selected and used for replacement.

Table 1: Input model parameters

Input type	Input model parameters					
	Period	*Probabilistic model*				Power factor
		α	β	C(A)	σ(A)	
Load	winter	1.67	4.07	60	4.42	0.95
EV	winter	0.49	0.07	12	1.16	1

CASE STUDY

The efficacy of the approach is demonstrated on a test residential LV feeder. The EV load, household load, and feeder models in the test case are detailed as follows:

EV load model

This study adopts an EV model used in [1], based on the charge characteristics of a BMWi3, prevalent in South Africa. Each household may have up to one EV and is connected to a 230V single-phase supply with a type-1 EV charger rated 12A. The maximum load is thus 2.76 kW. Several stochastic mobility factors including the distance traveled, time of arrival, time of departure, the EV rate of use, and battery capacity, and impact the EV SoC are applied in the EV load model. All uncertain variables are modeled using the beta PDF, and the PDF parameters are used as inputs in generating the EV model.

Customer load model

This study adopts load model parameters from [7] to model the diversity between customer loads and the variability across periods. Table 1 presents the beta PDF parameters for the EV and the customer loads at 7 pm. These are inputs to the HBE PLF analysis.

Feeder model

The feeder model used is characteristic of a residential low-density suburban area in South Africa, consisting of 21 customers uniformly spaced at 30 meters and is serviced by a 150kVA transformer. The initial and final properties of the feeder are shown in Table 2.

Testing procedure

The feeder is loaded incrementally with EVs in steps of 1 EV, running a nested MCS-HBE simulation at each penetration level. The feeder maximum demand (FMD), which describes the feeder's general loadability, is used in computing PV penetration levels, P (i), defined as:

$$\mathrm{P\ (i)} = \text{Total EV capacity} \times 100\%/\mathrm{FMD} \quad (9)$$

The initial feeder maximum demand is found to be 108.203 kVA.

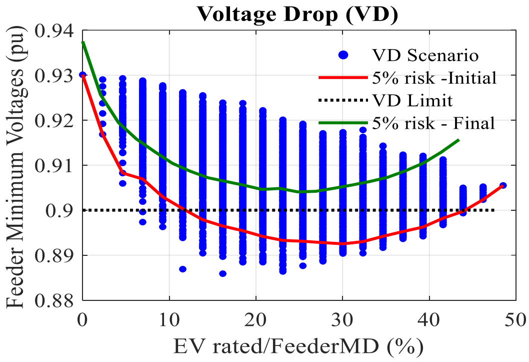

Figure 2: Feeder voltage drop performance

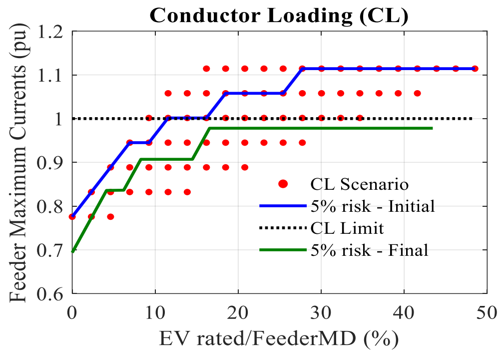

Figure 3: Feeder conductor loading

Results: feeder level analysis

The feeder response to the EV charging is demonstrated using scatterplots as illustrated in Figures 2 and 3. The scatterplots have several attributes including the initial feeder conditions without EVs, the different placement scenarios, the range of penetration, and the risk trendline indicating the 5% confidence-level performance under uncertainties. Voltage drop is seen to increase with penetration up to a minimum, representing scenarios with the highest voltage unbalance due to random EV allocation. Thereafter, further penetration may alleviate unbalance conditions, which improves voltage-drop conditions. The scatterplot for conductor loading demonstrates the impact of clustered and dispersed EV charging locations.

Based on voltage drop conditions, the initial feeder has an HC of 11.55%. A similar HC of 11.55% is arrived at based on the conductor loading limits. The extent of possible penetration depends on the available 'headroom' in the initial feeder design. Feeders operating close to the limits, either because of load growth or as designed, might not have any capacity for EV during peak periods. Such feeders will require substantial reinforcement.

The feeder response after the replacement of constrained conductors is shown by the green risk trendlines in Figures 2 and 3. The decreased range of the trendlines in the x-axis indicates the improved FMD or loadability of the feeder with larger conductors. This lowers the initial conductor loading to 0.7 from 0.8 pu. This can be interpreted using the knowledge that the initial conditions represent zero EV loading with a constant customer load and as such an increase in the conductor size lowers the loading level.

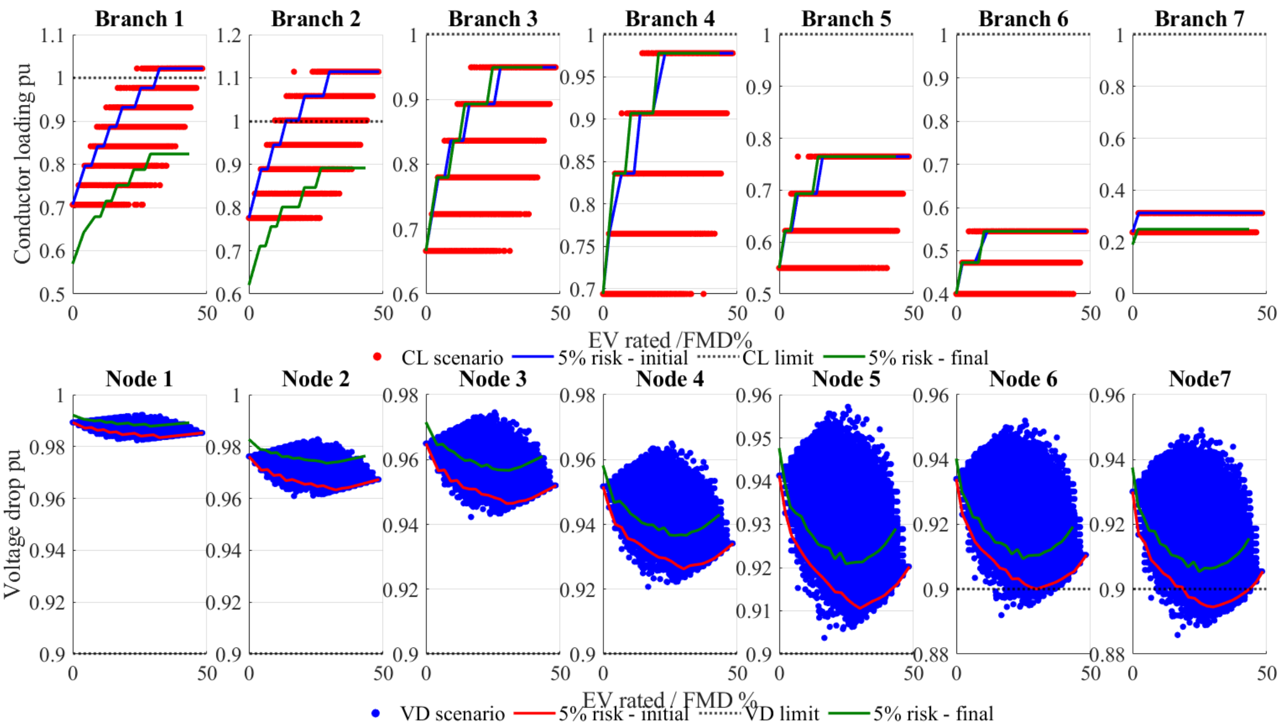

Figure 4: Feeder node and branch performance

Results: individual component analysis

Figure 4 shows the differentiated performance of each feeder element. The interpretation of the node and branch scatterplots is the same as that applied to the whole feeder. It is observed that nodes 6 and 7 record voltage drop violations since they are farthest from the source. Equally, branches 1 and 2 are overloaded due to their proximity to the source. These conductors are subsequently resized to comply with voltage and loading requirements. The green trendline indicates the risk-based performance of all conductors after reinforcement. The compliance of all components indicates the efficacy of conductor replacement as a reinforcement and HC enhancing strategy. It is noted that the FMD shifts to 120.85 kVA upon reinforcement and the final sizes of the conductors are recorded in Table 2.

The comprehensive results informing component performance under numerous scenarios – replicating the uncertainty in the problem – are beneficial not just for conductor resizing but also for other voltage and congestion support strategies. The benefits of such an approach are even more appreciable in complicated network designs with various spurs and mixed load types, where identifying segments that require voltage support and congestion relief is not as linear.

CONCLUSION

This paper demonstrates the application of a risk-based conductor resizing approach in the assessment of feeder conductor performance for residential networks with high EV penetration. Using the approach, the whole feeder and feeder section performance can be determined. The obtained results are relevant in several ways. Firstly, the limits of the whole feeder penetration can be assessed, and their performance determined. Secondly, the performance of each feeder element (nodes ad branches) yields granular results that are useful in the analysis of feeder section compliance, for operational and feeder reinforcement where possible. This can be used in planning for feeder voltage support or congestion management. Lastly, the approach considered the application of the conductor replacement as a reinforcement strategy. Where practically possible, such a process should consider the uncertainty from the allocation and the ToU resulting from the stochasticity of the e-mobility factors.

The results obtained show that compliance can be achieved through the conductor replacement process. This work is relevant for planners considering the connection of level-2 and level-3 chargers on the distribution networks where infrastructural upgrades become necessary because of higher power requirements. Further work is required to extend the application of the method to feeders with public and commercial EV fleets having different characteristics. Nevertheless, the work presented in this paper demonstrates the effectiveness of applying this approach in the analysis of high EV penetration and in the reinforcement process where possible.

Table 2: Initial and final feeder conductor properties

Conductor Properties	Feeder Section						
	1	*2*	*3*	*4*	*5*	*6*	*7*
x-section areas -Initial	50	35	35	25	25	25	25
x-section areas -Final	70	50	35	25	25	25	35

REFERENCES

[1] C. K. Rhoda, "A Comprehensive Methodology for Impact Assessment Studies of Energy Storage Systems on Low Voltage Distribution Feeders," Stellenbosch University, 2020.

[2] J. Quirós-Tortós, L. (Nando) Ochoa, and T. Butler, "How Electric Vehicles and the Grid Work Together," *IEEE Power Energy Mag.*, no. October 2018, pp. 64–76, 2018.

[3] K. Clement-Nyns and E. Haesen, "The impact of charging plug-in hybrid electric vehicles on residential distribution transformers," *2012 2nd Iran. Conf. Smart Grids, ICSG 2012*, vol. 25, no. 1, pp. 371–380, 2012.

[4] M. J. Chihota and B. Bekker, "New planning principles for distribution networks with penetration of distributed energy resources," in *6th IEEE International Energy Conference, ENERGYCon 2020*, 2020, vol. 2, pp. 643–648.

[5] S. Herbreteau, P. Georgiev, and M. Degache, "Debunking the myth of the grid as a barrier to e-mobility," Brussels, 2021.

[6] B. J. Coignard and P. Macdougall, "Will Electric Vehicles Drive Distribution Grid Upgrades ?," *IEEE Electrif. Mag.*, no. June 2019, pp. 46–56, 2019.

[7] L. Waswa, M. J. Chihota, and B. Bekker, "A Probabilistic Conductor Size Selection Framework for Active Distribution Networks," *Energies*, vol. 14, 2021.

[8] C. Rhoda, B. Bekker, and J. Chihota, "Probabilistic impact assessment of residential charging of electric motorcycles on LV feeders," *6th IEEE Int. Energy Conf. ENERGYCon 2020*, pp. 527–532, 2020.

[9] I. A. Ferguson and C. T. Gaunt, "LV network sizing in electrification projects - Replacing a deterministic method with a statistical method," *17th Int. Conf. Electr. Distrib.*, no. 68, pp. 1–6, 2003.

[10] M. J. Chihota, "Extending the Herman-Beta Transform for Probabilistic Load Flow Analysis of Radial Feeders," University of Cape Town, 2019.