Estimating Network Upgrade in MV Feeders with Machine Learning to Increase PV Hosting Capacity

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***Abstract*—Distribution networks worldwide are reaching their hosting capacity (HC) as photovoltaic (PV) connections increase, requiring utilities (aka distribution companies) to constantly assess HC and potential network upgrades. Traditionally, power flow simulations are used to calculate HC and/or upgrades. However, such simulations require reasonably accurate network models, which are not always available. This paper investigates the use of machine learning (ML) to estimate network upgrade in medium voltage (MV) feeders, increasing the HC of PV systems on MV-connected customers. Five ML algorithms are used to train ML models that estimate four response variables—HC, HC with upgrade, maximum reconductored feeder length, and average reconductored feeder length—related to both network upgrades and HC. The ML models are assessed in 143 real Brazilian MV feeders and results show that network upgrades and HC can be estimated without electrical models by using proper ML models.**

***Index Terms*—Distribution networks, hosting capacity, machine learning, medium voltage, network upgrade.**

I. Introduction

Distribution networks worldwide are reaching their hosting capacity (HC) as photovoltaic (PV) connections increase. This is driving utilities (aka distribution companies) to constantly assess HC and potential network upgrades (e.g., reconductoring) throughout their networks [1]. The traditional way of assessing HC and potential upgrades is by running power flows [2]. However, power flow simulations require accurate electrical models of the distribution networks, which are not always available [3]. For example, a utility may have accurate electrical models for a specific region but lack models for the entire service area [4, 5]; or a utility may not have any accurate electrical models at all. Therefore, techniques that do not fully rely on accurate electrical models should be developed to enable HC and upgrade estimation in regions where electrical models are unavailable, incomplete, or inaccurate.

Machine learning (ML) techniques have been showing good potential for estimating HC with reduced reliance on accurate electrical models. These ML techniques can be either fully independent of electrical models or partially reliant on them. Techniques that are electrical model-free typically use smart meter data alone to train the ML models [6, 7, 8]. In contrast, partially dependent approaches rely on data generated from power flow simulations, either by themselves [9, 10] or in combination with network characteristics [11, 12] (e.g., total impedance, feeder length, etc.) to train the ML models. Each ML technique is suitable for different situations, depending on the data available. If the utility has smart meters but lacks electrical models, smart-meter-based ML techniques are more appropriate. If smart meter data is unavailable, and some accurate electrical models exist, ML techniques that are partially dependent on electrical models are more appropriate. The latter applies in two key situations: a) when a utility has accurate electrical models for only part of its network, these could be used to train ML models capable of estimating HC in areas without such models; and b) this concept could also be applied between utilities, where one company with accurate electrical models could train ML models that another company—lacking such models—can then use to assess HC in its own network.

So far, no work has been identified exploring the use of ML to estimate network upgrade to increase HC of PV systems in medium voltage (MV) feeders. As such, the contribution of this paper is to solve this gap. Also, besides estimating network upgrade, ML models that estimate the new HC after the upgrades are proposed. For training, network characteristics and power flow simulations are used. For validation, the performance of ML models is assessed on hundreds of real Brazilian MV feeders which together feed 460,000 customers through more than 17,000 km of MV lines.

II. Estimating Hosting Capacity and Network Upgrades via Machine Learning

The initial application of ML in HC analysis did not involve direct estimation of HC values. Instead, ML techniques were employed to classify distribution network feeders based on their characteristics. This approach enabled the selection of a limited number of representative feeders, which could then be used to perform HC assessments. The results of these assessments were extrapolated to a broader set of feeders—based on their similar characteristics—across the entire distribution network. This was first done for MV feeders (4kV-33kV line-to-line) in the United States of America [13] and later to low voltage (LV) feeders (230V line-to-neutral) in the United Kingdom [14].

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TABLE I. MACHINE LEARNING ALGORITHMS USED TO TRAIN THE HOSTING CAPACITY AND MV FEEDER UPGRADE MODELS

Machine Learning Algorithm	Complexity	Interpretability	Linearity	Robustness	Computational Cost
Linear Regressor (LR) [15] [16]	Very Low	Very High	Linear	Low	Very Low
Huber Linear Regressor (HLR) [15]	Low	High	Linear	High	Low
Decision Tree Regressor (DTR) [15] [16]	Low/Moderate	Very High	Nonlinear	Low	Moderate/High
Random Forest Regressor (RFR) [15] [16]	Moderate/High	Moderate/Low	Nonlinear	High/Moderate	High
Support Vector Regressor with Kernel Approximation (SVR) [15] [16]	High	Low	Nonlinear	Moderate	Moderate/High

More recently, direct estimation of HC using ML was proposed in [11, 12]. Both studies trained ML models using characteristics of LV feeders—distinct for each study—and stochastic power flow simulations. While [12] employed only Linear Regression, [11] assessed multiple ML techniques and identified Random Forest as the most accurate for HC estimation. However, both studies focused exclusively on HC estimation. Their ML models do not address the estimation of required network upgrades—to increase the current HC—or the prediction of updated HC values following such upgrades. The rest of this section introduces ML models designed to bridge this gap.

A. *Machine Learning Algorithms and Trained Models*

This work estimates the HC and upgrades on MV feeders by exploring five ML algorithms, which main characteristics are presented in Table I. For each of the ML algorithms presented in Table I, four distinct ML models are trained. Each model is designed to estimate response variables from a set of 10 predictor variables, which are selected from hundreds of available predictor variables. The predictor variables are network physical characteristics extracted from the network models. While the response variables used for the training of the ML models come from power flow simulations (detailed in Section III-A). The four response variables are described as follows:

- <u>PV Hosting Capacity (HC)</u>: the maximum PV HC (MW) for each possible connection location on the MV feeder.
- <u>PV Hosting Capacity with Upgrade (HCwU)</u>: the maximum PV HC (MW) achieved after upgrades for each possible connection location on the MV feeder. Note that reconductoring is the only upgrade considered.
- <u>Maximum Reconductored Feeder Length (MRFL)</u>: the maximum reconductored feeder length (km) among all tested sizes of the PV system for each possible connection location on the MV feeder.
- <u>Average Reconductored Feeder Length (ARFL)</u>: the average reconductored feeder length (km) among all tested sizes of the PV system for each possible connection location on the MV feeder.

These response variables serve distinct yet complimentary roles in the network planning. HC is primarily used to evaluate PV connection requests, indicating whether a specific bus has spare capacity to accommodate the request, and to support long-term network planning, indicating whether a feeder is close to its maximum capacity. HCwU becomes relevant when a customer requests to connect a PV system, but the existing network lacks sufficient capacity. In such cases, HCwU estimates the HC assuming the customer is willing to pay for the necessary network upgrade. Meanwhile, MRFL and ARFL are valuable for macro-level network planning. They provide estimates of the maximum and average conductor lengths that would need to be installed to enable network-wide HC expansion, which can be used to estimate investment costs.

B. *Selection of Predictor Variables*

A total of 415 candidate predictor variables is investigated for selection. The ML models proposed in this paper are designed to estimate the response variables by using only a subset of 10 predictor variables, making the selection process a critical challenge. The decision to reduce the number of predictor variables was made to prevent irrelevant or highly correlated variables from increasing computational time for training and inference, and to minimize the risk of overfitting the ML models. Therefore, the selection aims to identify predictor variables that exhibit strong relevance to each specific response variable, which was determined in this paper by the Gini importance metric [15]. This is automatically determined by applying a simple decision tree algorithm for each response variable and verifying the earliest selected features for splitting the tree, which are considered the most important. Note that the selected predictor variables can differ for each response variable.

C. *Selection of Hyperparameters*

Three of the ML algorithms used in this paper—Decision Tree Regressor, Random Forest Regressor, and Support Vector Regressor—require hyperparameter tuning. Hyperparameters are selected via random search, using randomly sampled combinations from predefined values. Grid search was also considered and tested, but it performed worse than the random search. Advanced hyperparameter optimization, such as the Bayesian optimization, could be better investigated in future works.

Model performance is evaluated through cross-validation (k-folds), where 80% of the data is split into two-thirds for training and one-third for testing. This process is done three times by alternating the one-third part for each cross-validation. The best hyperparameter configurations are identified using Mean Absolute Error (MAE) and are used to estimate the response variables for the assessment stage.

III. ASSESSMENT OF THE MACHINE LEARNING MODELS

This section presents the traditional HC and network upgrade calculation method as the benchmark and the source of data for training the response variables, alongside the metrics used to compare it with ML-based estimates.

A. *Power-Flow-Based Calculations*

This is the traditional way of calculating HC and network upgrades, which involves carrying out multiple power flows with increasing PV penetration. This method is accurate, so it is used to validate the proposed ML models. It is also used to create a training set for the response variables. Nevertheless, it

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requires correct electrical network models (e.g., phases connections, topology, impedances), and it is simulation intensive. This work calculates the HC and upgrades via power flows—using the DSS Extensions [17], an alternative implementation of EPRI's OpenDSS [18]—for every possible PV system installation location on an MV feeder, as shown in Fig. 1.

In Fig. 1, for every possible PV system installation location, n, it is calculated the PV hosting capacity, HC, the PV hosting capacity with upgrade, HCwU, the maximum reconductored feeder length, MRFL, and average reconductored feeder length, ARFL. To do so, an initial PV size, P_i^{PVsize}, is set, for iteration i. This PV size is incremented by a pre-defined step, P^{PVstep}, along with the iterations, until it gets to a pre-defined maximum PV size, P^{PVcap}, or a pre-defined maximum upgrade.

Focusing on the MRFL, for each MV feeder, PV size and location, a power flow is run, and voltage and congestion issues are assessed. In case of issues, reconductoring is carried out incrementally, segment by segment, along the critical path. Once there are no more issues, the maximum reconductored feeder length is recorded. Note that every increment is reassessed via power flow, as in Fig. 1, and the maximum available conductor size is always used—an assumption adopted by a Brazilian utility considering the current rate of load and new generation connection. For the ARFL, the core concept and assumptions are the same as for the MRFL, but here, the average length is recorded rather than the maximum length.

Note that the HCwU, MRFL, and ARFL are related to network upgrades. So, if no upgrade is required, by default the HCwU receives the maximum possible rated power (e.g., 3MW), and both MRFL and ARFL receive zero.

B. Assessment Metrics

Results of each ML model will be compared to results from the power-flow-based calculations to assess ML models' accuracy. For this the following metrics are used:

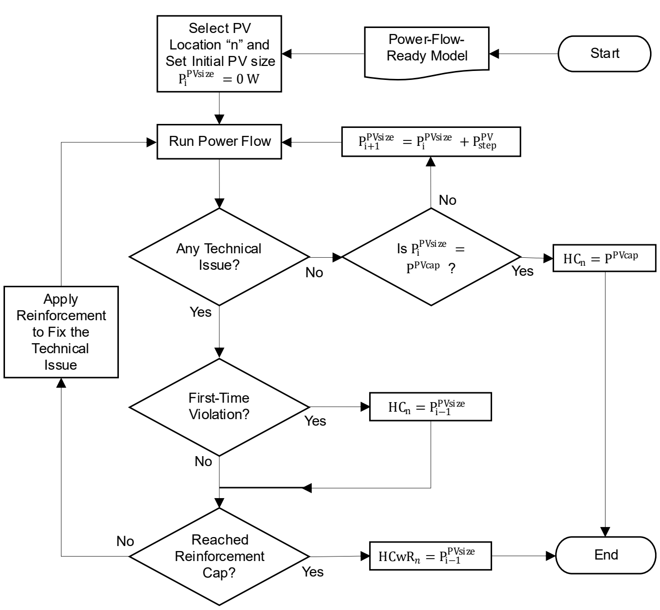

Figure 1. Flowchart for the Power-Flow-Based Calculations for every possible PV installation location.

- Mean Absolute Error (MAE): the MAE for the given ML model is the mean absolute error of all locations in all MV feeders considered in the study. It can vary between zero and infinite. Values closer to zero means the ML model is more accurate.
- Root Mean Square Error (RMSE): the RMSE for the given ML model is the root mean square error of all locations in all MV feeders considered in the study. It can vary between zero and infinite. Values closer to zero means the ML model is more accurate.
- R^2: subtract from 1 the squared ratio of the RMSE to the variance of the power-flow-based value. It is dimensionless, making it suitable to compare the different response variables. It varies between minus infinite and +1. Values closer to 1 means the ML model is more accurate.

IV. Case Study

The accuracy of the proposed ML models is assessed in a case study with two parts. The first part uses a single real MV feeder (11.4kV) with a PV system to be installed in a pre-defined bus, making it easier to explain how this accuracy assessment is carried out in a simpler case. Then, in the second part, the study is expanded to 143 real MV feeders, with the PV system having multiple buses as possible installation location, which is a much more complex and comprehensive study. In both cases (1 MV feeder and 143 MV feeders) the benchmark is the power-flow-based calculations, which uses integrated MV-LV feeder models for each MV feeder. Network models follow the Brazilian Electricity Regulatory Agency (ANEEL) requirements [19], guaranteeing modeling fidelity.

A. Real MV Feeders

The summary of key feeder statistics is given in Table II for both case studies. Note that the feeders have residential, commercial and industrial customers, and many of them have in-line voltage regulators and capacitor banks.

As these MV feeders are located in Brazil, Brazilian rules/statutes are used for voltages and thermal limits. The Brazilian upper limit for voltages at this voltage level is 1.05pu. Lines current limits follow each cable size, as per its datasheet. Transformer overloads are limited to 180%, their temperatures are limited to 140°C, and their minimum estimated lifespan cannot be below 20 years.

B. Selected Predictor Variables

Independently of the MV feeder, from the 415 candidate predictor variables only 28 were chosen to estimate the four response variables. The full selection list is given in [20], but, for compactness, only the key one is presented here:

Positive-sequence resistance of the Source-PV path (Ω): represents the electrical distance between the bus where the

TABLE II. KEY FEEDER STATISTICS FOR EACH CASE STUDY

Key Statistics	Case Study 1	Case Study 2
No. of MV Feeders	1	143
Total Length (km)	234	18,000
No. of Customers (total)	2,843	460,000
Urban Customers (%)	73%	95%
Rural Customers (%)	27%	5%

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represents the electrical distance between the bus where the PV system is installed and the head of the feeder. Its selection is justified by the strong correlation between voltage rise and the product of the Source-PV path resistance and the PV installed capacity.

C. Results Analysis for a Single MV Feeder

The results for a single real MV feeder, with a PV system to be installed on a pre-defined bus around 9km from the substation, are given and discussed in this section.

In this part of the study the ML models' accuracy is assessed by the difference in response variable values between power-flow-based calculations (the benchmark) and each ML model, as shown in Table III—color coded based on the percentage error, from small to high, in the sequence green-yellow-orange-red. It can be observed that the ML models based on Decision Tree Regressor (DTR) and Random Forest Regressor (RFR) were particularly accurate with estimation errors below 2% for response variables related to upgrades (i.e., HCwU, MRFL, and ARFL). For the HC estimation these ML models still performed well, but with errors up to 8%. Nevertheless, these errors are always conservative, i.e., the HC capacity is smaller than the real one, meaning that the network should be safe for these estimations. Note that the higher accuracy observed in the three upgrade-related response variables may be attributed to the use of maximum conductor size, which reduces data variability, hence, simplifying the estimation process. In overall, results show that well-trained ML models can give good estimations for the HC, HCwU, MRFL, and ARFL.

D. Results Analysis for All MV feeders

In this section, the ML models' accuracy is assessed for all 143 real MV feeders, with the PV system having multiple buses as possible installation locations along the feeder backbone—only excluding locations/buses unable to host PV systems even with maximum conductor upgrade. The results are depicted in Table IV and comprise the MAE, RMSE and R^2 metrics, which are color coded based on the accuracy, from high to small, in the sequence green-yellow-orange-red. It is possible to observe that the Random Forest Regressor (RFR) is the most suitable ML algorithm for all four response variables, according to the three metrics. The highest performance was achieved by the PV HCwU, with an R^2 of 0.98. The second-best performance resulted in a tie between PV HC and MRFL, both with an R^2 of 0.94. The ARFL ranked third with an R^2 of 0.91. The values of MAE and RSME also confirm the above, but they are not mentioned here for brevity. This result is consistent with the single MV feeder case, but the increased diversity of MV feeders caused the DTR to lose accuracy, performing noticeably worse than the RFR in the larger case study.

To give more details on the results, Fig. 2 presents box plots comparing the ML models estimations for hosting capacity (HC) and HC with upgrade (HCwU), while Fig. 3 presents box plots comparing the ML models estimations for maximum reconductored feeder length (MRFL) and average reconductored feeder length (ARFL). Both figures clearly show that the DTR and RFR can capture limits imposed by rules/statutes (i.e., maximum HC of 3MW, as per Brazilian rules for non-dispatchable mini-generation) and they do not return impossible values (i.e., negative reconductored feeder length), while the other three ML algorithms fail to respect these limits. This shows that DTR and RFR not only provide more accurate estimations but also reliable ones, respecting rules and common sense.

TABLE III. DIFFERENCE IN RESPONSE VARIABLE VALUES BETWEEN POWER-FLOW-BASED CALCULATIONS (REFERENCE) AND EACH ML MODEL

Response Variable	PF	LR	HLR	DTR	RFR	SVR
HC (MW)	0.60	1 (+67%)	0.96 (+60%)	0.55 (-8%)	0.55 (-8%)	0.54 (-10%)
HCwU (MW)	1.60	1.95 (+22%)	1.97 (+23%)	1.6 (0%)	1.6 (0%)	1.75 (+9%)
MRFL (km)	86.53	70.15 (-19%)	52.92 (-39%)	86.50 (~ 0%)	86.56 (~ 0%)	67.85 (-22%)
ARFL (km)	79.70	77.67 (-3%)	55.57 (-30%)	78.98 (-1%)	79.60 (~ 0%)	28.61 (-64%)

TABLE IV. ASSESSMENT METRIC VALUES FOR EACH ML MODEL

Response Variable	Metric	LR	HLR	DTR	RFR	SVR
HC (MW)	MAE	0.61	0.60	0.16	**0.13**	0.43
	RMSE	0.72	0.72	0.36	**0.25**	0.58
	R^2	0.50	0.50	0.87	**0.94**	0.67
HCwU (MW)	MAE	0.48	0.47	0.08	**0.06**	0.31
	RMSE	0.60	0.61	0.20	**0.11**	0.41
	R^2	0.56	0.55	0.95	**0.98**	0.80
MRFL (km)	MAE	22.38	20.56	4.65	**3.57**	15.44
	RMSE	29.50	30.26	14.24	**8.78**	24.41
	R^2	0.31	0.27	0.84	**0.94**	0.53
ARFL (km)	MAE	17.92	16.51	8.67	**4.60**	14.61
	RMSE	24.69	25.39	15.18	**8.98**	24.13
	R^2	0.31	0.27	0.74	**0.91**	0.34

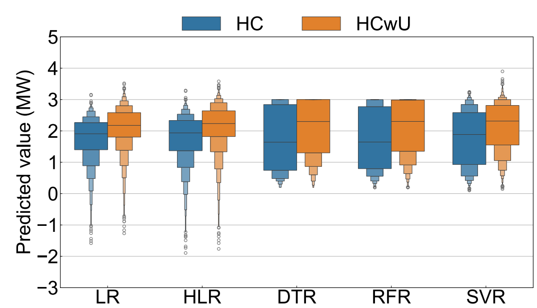

Figure 2. Distributions of HC and HCwU predicted values for each ML model.

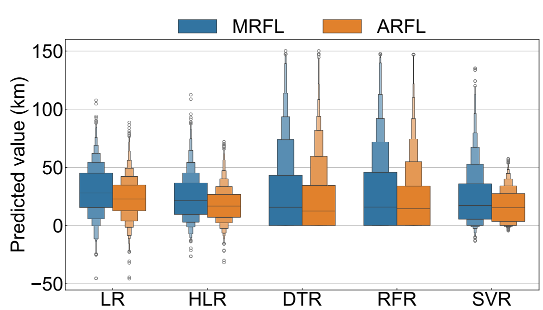

Figure 3. Distributions of MRFL and ARFL predicted values for each ML model.

E. Discussions on Practical Application

Some utilities may lack accurate electrical models across their entire service area, limiting the use of traditional power flow analysis. In such cases, ML models trained on well-modeled regions can be applied to estimate network upgrades and HC in areas without electrical models. Where accurate electrical models do exist, power-flow-based methods is still preferred due to their precision. Additionally, for companies without any accurate electrical model, a practical alternative is to partner with utilities that have already developed ML-based HC and upgrade estimation tools. In this way they can apply the shared ML algorithms to their own networks.

Note that accurate estimation of HC and network upgrades is essential, as it directly influences utilities planning and investment decisions. Thus, ensuring the use of proper ML models is crucial to prevent customers from being negatively affected—by bearing the cost of unnecessary infrastructure or by facing restrictions to connect new PV systems. It is also crucial to ensure that the characteristics of the network under consideration do not stray too far from the training dataset, as extrapolation is typically not well captured by ML models.

In the context of Brazil (and likely to other countries as well), utilities are required to carry out technical studies for MV PV connection requests to assess whether network upgrades are needed, making upgrade estimation essential. When existing infrastructure lacks capacity, estimating HC with Upgrade (HCwU) helps to determine how much generation can be added if the customer funds the necessary improvements. Additionally, metrics like Maximum and Average Reconductored Feeder Length (MRFL and ARFL) support broader planning by estimating the scale of infrastructure expansion and associated investment needs for a potential network-wide HC expansion.

V. CONCLUSIONS

This paper covers the gap in the use of ML to estimate network upgrades in MV feeders due to PV systems connection requests, increasing the HC of PV systems on MV-connected customers. It also investigates the estimation of HC before and after upgrades. Five ML models were proposed and assessed on 143 Brazilian MV feeders, with Random Forest Regressor showing the highest accuracy. Results show that rough estimations of network upgrades and HC can be achieved without electrical models, provided adequate ML methods are used. Future work may consider extending the proposal to LV networks and integrating other distributed energy resources.

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