Distributed Generation Hosting Capacity Evaluation for Distribution Networks Considering Uncertainty

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Received: September 9, 2022. Revised: February 13, 2023. Accepted: March 2, 2023. Published: March 29, 2023.

Abstract— The use of grid systems for distributing and managing resources such as computing power and data storage has become increasingly widespread in recent years. However, as the demand for these resources continues to grow, the capacity of traditional grid systems to meet this demand has become a concern. When dealing with the constantly expanding system scale and its many uncertainties, traditional model-based techniques are becoming unsuitable. A better alternative to these techniques involves considering data-driven control (DDC) methodologies.

In this paper, we begin by reviewing the current state of the art in DDC usage in grid systems in monitoring, improving, error detection, etc. with a particular focus on improving host capacity. We then describe our proposed approach, which involves improving the host capacity of grid systems using historical data. Finally, we present experimental results demonstrating the effectiveness of our approach and discuss its potential impact and future directions.

Keywords—Hosting Capacity Analysis, Data-Driven Control, host capacity optimization, resource allocation

I. Introduction

The generation, transmission, and distribution components of power grids are constantly evolving, and this impacts the planning and management of the smart grid. Power grids are currently becoming increasingly complex as a result of three factors: new hardware, new data sources, and more stringent social and environmental standards. The evolution of the electrical grid is being pushed by these three forces in technology, markets, and public policy.

The amount of additional production or consumption that may be connected to the grid without negatively affecting the dependability or voltage quality for other consumers is known as the hosting capacity (HC), [1], [2]. The network demand profile, generator dispatch profile, operating reserve, diversity and variation factors of PV systems, step load capabilities of generators, generator startup, and minimum run duration, etc. must all be taken into consideration in the HC estimation, [3].

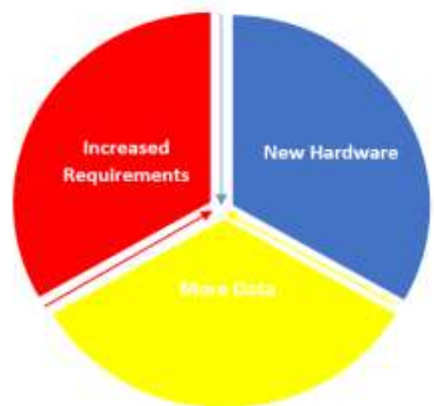

Figure 1. Factors pushing the advancement of Electrical Grid

As a result, steady-state analyses serve as the basis for most HC evaluations that have been presented in the literature. The reference parameter, network conditions, topology, location, and PV deployment situation can all affect how HC behaves. As a result, HC is not a unique value and is highly dependent on the proper choice of the aforementioned performance measures and their bounds. [4], gives a methodical and thorough introduction to the study, creation, assessment, and improvement of HC. [5], provides a classification of HC quantification techniques and completes a thorough analysis of three different HC quantification techniques. In addition to performing a similar review, [6], also provided a summary of the current techniques being used in HC analysis. The factors pushing the advancement of Electrical Grid are presented in Figure 1.

Future distribution grids will be built on DERs, which include wind generators, solar photovoltaic (PV) generators, energy storage systems, etc. This is due to the fact that implementing such technologies can decrease greenhouse gas emissions, lower energy costs, lessen reliance on fossil fuels, improve distribution efficiency, and satisfy rising energy demands, [7]. The rapid adoption of solar, wind and electric vehicles has all been a result of the social and environmental aims of eco-friendly energy and the understanding of climate change.

The U.S. Environmental Protection Agency (EPA) predicts that, after natural gas, renewable energy sources will overtake coal and nuclear power by 2040, [8], [9]. A number of variables, including voltage magnitudes, feeder power flows, and power quality concerns, are used to quantify operational performance. The modern grid is a complex system that requires reliable and efficient operation to meet the increasing electricity demand. Distributed grid systems allow their users to access and use shared Distributed Energy Resources (DERs) especially distributed photovoltaics (DPV). Such setup presents the associated possibility of adverse grid impact hence, the need for DER impact studies and of particular interest the grid hosting capacity, [10]. [11], states that running reserve policy, sustaining supply quality, legacy infrastructure, and other issues might be significant hurdles for distributed PV-diesel electricity networks. Different switching processes have a significant impact on the network as PV's market share rises, [12].

One key aspect of ensuring reliable operation is ensuring that the grid has sufficient host capacity, or the ability to generate and transmit electricity to meet demand. In recent years, there has been a growing interest in using data-driven (DD) techniques in enhancing the performance of power systems in general.
The 21st century has seen a surge in the growth of data science becoming an important solution to the issues of scalability and uncertainty. Big data has made a critical component of this, finding applications in particle physics, [13], and process engineering, [14], which have witnessed a major shift from model-based approaches to DD techniques.
In this paper, we will review the current state-of-the-art applications of DD techniques and propose a potential approach for further improving host capacity through the use of historical data.

This research aims to examine the entire structure of real low-voltage grids in terms of hosting capacity for distributed generators (DG) using machine learning.

In this paper, a novel method for determining a time-varying hosting capacity behavior through temporal instants is presented. Hence, necessitating the adoption of a Recurrent Neural Network (RNN) in the form of Long Short Term Memory (LSTM). This method of extended hosting capacity can more accurately depict the system's internal and external changes over time, such as the effects of harmonic distortion and voltage rise brought on by non-linear loads and DERs

The remainder of the paper is structured as follows: A background of the current state of data-driven approaches in the context of energy systems is provided in section 2. The methodological underpinnings of our approach are described in Section 3: a data-oriented hosting capacity analysis approach is presented. The results of various tests are presented in Section 4, with an emphasis on applicability as well as classification accuracy. The main findings are outlined in Section 5.

II. LITERATURE

Power system analysis and control have a long history of using machine learning and artificial intelligence. Machine learning was first used in power systems at the beginning of the 1990s to diagnose system faults, including fault detection and fault categorization, [15]. However, because of the computing power available at the time, the majority of machine-learning techniques were simply employed to supplement the knowledge of human specialists.
The benefits of using ML for host capacity optimization are numerous. For example, ML algorithms can learn from historical data and make predictions about future electricity demand, allowing grid operators to anticipate and plan for changes in demand. ML algorithms can also identify patterns and trends in data that may not be immediately apparent to humans, enabling more accurate forecasting and planning. Additionally, ML algorithms can be trained to optimize grid operation by identifying and mitigating potential bottlenecks or vulnerabilities in the system.

Several approaches have been proposed for using ML to improve host capacity in the grid. These approaches can be broadly categorized into two main categories: demand-side management and supply-side management.

Demand-side management approaches aim to optimize the use of electricity by consumers, typically through the use of smart meters and other Advanced Metering Infrastructure (AMI), [16]. These approaches use ML algorithms to forecast electricity demand and optimize the operation of appliances and other electrical devices to reduce overall consumption. For example, a demand-side management system might use ML to predict the likelihood that a household will need to use an air conditioner on a hot day and adjust the operation of the air conditioner accordingly to reduce energy consumption, [17]. Numerous other methods for studying demand-side optimization have been examined. For instance, a multi-objective genetic algorithm technique has been developed, [18], for executing Demand Side Management (DSM) operations in an automated warehouse. The scheduling of direct demand management tactics has also been improved using a modified genetic algorithm, [19]. A demand-side energy management system based on game theory that is autonomous and distributed has also been presented, [20]. Additionally, [21], built an autonomous DR system that aims to be both optimal and fair with regard to the players that are engaged. A fuzzy logic strategy for reducing the load in household Heating, Ventilation, and Air Conditioning (HVAC) systems has also been given, [22]. It makes use of Wireless Sensor Networks (WSN) and smart grid incentives analyzed using various situations, [23]. In [24], a conceptual framework is presented for setting up data analytics operations and fostering data-driven decision-making in an electricity distribution network.

Supply-side management approaches, on the other hand, focus on optimizing the generation and transmission of electricity. These approaches typically use ML algorithms to forecast electricity production and optimize the operation of power plants and transmission lines to meet demand. For example, a supply-side management system might use ML to predict the output of a solar power plant based on weather data and adjust the operation of the plant accordingly to meet demand. The literature on energy exchange among Microgrids (MGs) is extensive. [25], presents an overview of game theoretic techniques for MGs. Assuming that the system model is known, this review investigates both cooperative energy-sharing models and non-cooperative game models for distributed control of MGs. [26], investigates energy sharing across MGs with the goal of lowering energy expenses. This work is later expanded to MGs taking into account the price-based demand response, [27].

Supply-side management is the main topic of this article, with the objective of giving an analysis of hosting capacity in real-time. Current HC analysis techniques are divided into four groups, [28]. The worst-case HC is calculated using the deterministic technique, [29], [30].

Without taking into account the many details of an actual power system, the obtained HC value is understated and uncertain. The stochastic method employs a Monte-Carlo-based strategy to account for power system uncertainties, such as arbitrary PV unit location and load size, [31]. The calculation time and increased complexity of the power system and uncertainty factors are two disadvantages of this well-liked approach.

The time series approach applies created time-series data to simulations and may alternatively be thought of as a deterministic method, [32]. While ensuring that the operational restrictions of the distribution network are met, the optimization-based approach aims to maximize the active power injection of DGs into the distribution network. To achieve the best result, this approach must go through several iterations.

We used a machine learning-based strategy for HC analysis after considering how to solve these challenges. To distinguish dynamic hosting capacity (DHC) analysis from static snapshot hosting capacity, we first build a data-driven machine learning problem model that will help distribution system operators better determine hosting capacity, optimize control, and dispatch DERs in real time.

Consequently, our work is closely connected to and may be viewed as a refinement of the work done by [4], [16]. They provide ways for distinguishing distribution grids by an examination of grid attributes of practical importance (e.g., distribution of rated transformer power). In contrast to our methodology, they do not categorize grids based on their DG hosting capability, but instead, analyze the characteristics of a large number of real-world grid designs.

Overall, the method we employ ML algorithms to analyze low-voltage grids is novel.

III. METHODOLOGY

Since we aim to calculate HC in real time with high accuracy, the previous HCA methods cannot meet the requirements. Instead, we propose a machine learning-based problem formulation, [33]. This formulation uses historical time-series data to conduct offline training and obtain the HC value based on real-time system conditions. Specifically, we model HCA as a supervised learning problem that uses data of power system features and operating conditions as the input vectors and HC data as the target labels. To achieve such a learning target, the mapping from historical data on different input features to the HC is highly nonlinear, and deep learning is a promising method to deal with the non-linearity. To capture the periodic pattern of the power system, e.g., hourly, daily, and yearly patterns, we use the recurrent neural network (RNN) as the basic learning framework, [34]. In such a model, RNNs need some past context to predict the current output, but in practice, it can hardly capture the relationship in a long sequence. One of its variants, the long short-term memory (LSTM), has a much better performance of extended learning. An RNN cell's input is divided into two halves. The first is the output of the previous cell, hidden state h_{t-1}, and the second is the input vector for this cell, x_t. In this manner, an RNN may use its internal state (memory) to process input sequences. The network may be taught repeatedly by sending information through these repeating cells. Each RNN cell will produce h_t as,

$$h_t = ø(W[(h_{t-1}, x_t]) + b)$$

where ø (.) is the activation function used to extract non-linear functions.

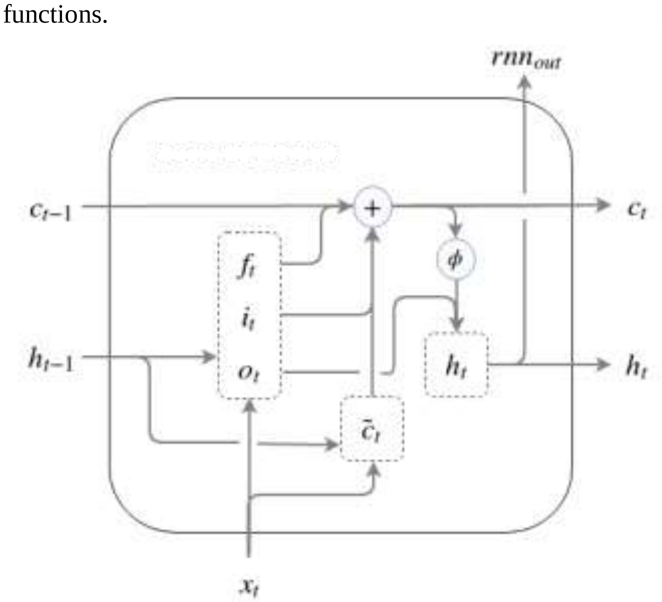

Figure 2. Basic Cell of LSTM

RNNs are meant to analyze sequential data, however, they have limitations for HCA. One problem is that RNNs cannot reliably transmit data between two cells that are separated by considerable distances. To address this issue, LSTMs enhance simple RNNs with gate functions capable of learning both short-term and long-term dependencies, [35]. This gate design also prevents gradient from inflating and disappearing, which is a significant disadvantage of RNNs, [35]. As a result, LSTMs have shown to be useful models for sequential prediction issues.

We make use of data taken from the Mendeley Data Portal to prepare training and testing data for validation, [36]. The basic cell of LSTM is presented in Figure 2. The data is low-voltage grid data generated from a reference network model, i.e., simulations on MATLAB, and primary data processed on QGIS. The reference network model creates synthetic low-voltage grids using data that is publicly available as well as national norms and standards. Furthermore, it provides information on household solar PV hosting capacity in low-voltage networks. The databases are high-resolution (1 x 1 km) data from the UK, Sweden, and Germany and contain data on energy peak demand, the proportion of the population living in flats, and essential grid metrics like transformer capacity, maximum feeder length, and home solar photovoltaic hosting capacity estimates. Figure 3 below shows the hosting capacity expressed as annually produced electricity in each cell (kWh/household/year) in Sweden (A), Germany (B), and the UK (C). This shows that the highest capacity is in Sweden and the lowest in Canada.

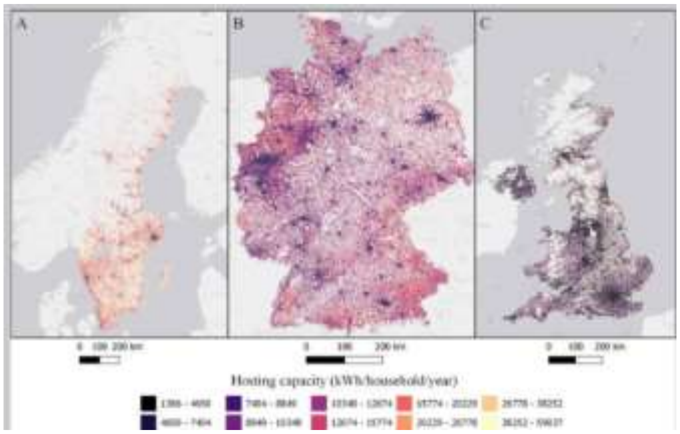

Figure 3. Hosting Capacity in Sweden, Germany, and the UK respectively

Hosting capacity for all low-voltage grids in each country, as well as an estimate of national low-voltage hosting capacity, with sensitivity, runs in parentheses, for household solar PV to be installed. 33 (+5/-7) GW (Sweden), 248 (+5/-24) GW (Germany), and 63 (+1/-14) GW (United Kingdom).

Grid component datasets are uncommon, and the dataset may be used to examine grid impacts from various home end-use technologies, as well as serve as a baseline for other reference network models.

Time-series models are used to capture temporal sequence by LSTM. We enter the power flow data from the power flow analysis of the all-time series at one bus in each training step, and the output is the HC data vector for all the time series on this bus. As our input vector, we use the Load Flow analysis result. We use voltage magnitude, voltage angles, load profiles, PV profiles, and other parameters. The h_t of each cell represents the HC value. We use the min-max normalization strategy to preprocess the input vector. The lowest and highest values of each feature in the input vector are transformed to 0 and 1, respectively. All other values are converted to decimal integers between 0 and 1. For the HC data, we instantly scale the value using a predetermined constant. Using this linearity scaling technique, we can easily extract the result to the appropriate HC value. A list of all the datasets and their related variable names is presented in Table 1.

Table 1: List of all datasets and their related variable names

Dataset	Variable name
Share of the population living in apartments	FracAPT
Peak residential load demand (kW/sqkm)	Demand
Maximum feeder length (km)	Feeder
Number of customers on the longest feeder	CustPerFee
Hosting capacity (kW/sqkm)	Cap
Hosting capacity (kW/household)	CapPerCust
Hosting capacity (kWh/household)	EnergyHH
Number of transformers	TrNumber
Capacity of transformers (kVA)	TrCap
Household customers per transformer	CustPerTr

IV. RESULTS

The first set of analysis examined the impact on the calculation of the DHC(t) by using the measurements of the system. The correlation between the data measurements of generated power and the maximum power generation was calculated, tested, and plotted for all the days in the week of measurement. That is, for all measured values of generated power, a maximum amount of power generation was calculated, creating a linear dependency, which linear regression using the y = ax + b formulation is shown in Figure 4.

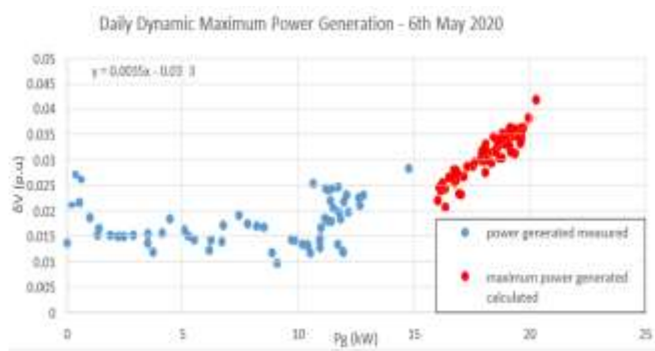

Figure 4. Voltage variation x generated power and the linear dependency in relation to the maximum amount of power calculated by (5)—May 06, 2020.

If a linear extrapolation is created using these points, it is possible to determine the hosting capacity when the calculated line crosses the overvoltage limit index at 5%. For example, for May 06, 2020, the linear regression found regarding the maximum amount of power calculated is equal to y = 0.0035 x − 0.0333, where the variable y represents the overvoltage margin of the system, and x represents the calculated power for any overvoltage margin considered. A linear correlation is calculated for all these instants of time using the overvoltage margin as well as the measured power from the PV. These factors will be responsible for this result. Taking a look at Figure 5 where an exemplification of the calculation of the daily DHC(t) is given. As in the local hosting capacity method, when these lines cross the limit index at 5%, a group of lines will be drawn as a result of the hosting capacity value. These lines are created due to the existence of the ordered pairs: The measured pair (δV, P_g) and the calculated pair (δV_{max}, P^{max}). It is important to notice that all ordered pairs are related by an instant in time. In Figure 5, as an example, we have defined two ordered pairs to illustrate the method. For each ordered pair, as mentioned before, we will extend those lines until they reach the limit index set as 5% of the overvoltage margin. In the example, the purple line created by the first ordered pair will reach a hosting capacity value of 5% of the maximum overvoltage margin of 25 kW. On the other hand, the yellow line created by the second ordered pair will reach 23 kW of hosting capacity for a certain instant in time. Based on this methodology, we will repeat the procedure for all ordered pairs created. Thus, the daily DHC(t) profile for May 6th is shown in Figure 5.

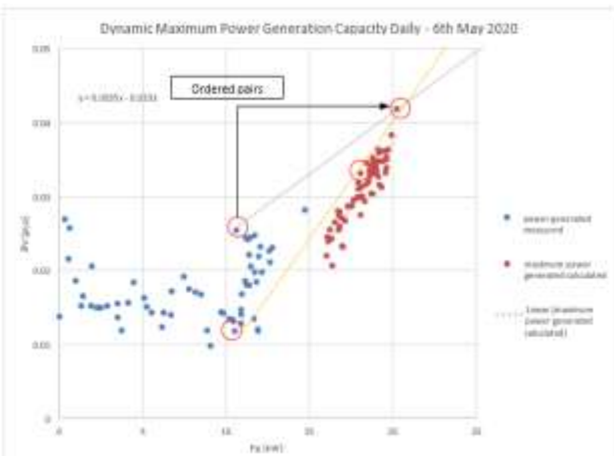

Figure 5. Exemplification of calculation of dynamic daily hosting capacity in relation to May 06, 2020.

In figure 5 the average score for the 6th of May, was 24 kW, as calculated through the daily DHC(t) profile. Remarkably, some values of hosting capacity are slightly higher and lower than the average. These phenomena might have occurred because some external and internal factors contributed to these differences. In this case, the maximum daily hosting capacity is 16.9 kW, whereas the minimum value is 18.3 kW. In relation to one of the highest values, it is possible to offer an explanation. This result is only significant at a moment when there is almost no solar production because it is early in the morning or clouds are covering the panels. Thus, the voltage rise will be low due to the lack of solar production, coupled with the fact that the building is empty. For example, one of the highest DHC(t) found was at 12 p.m., which is defined as lunchtime, and all the building's equipment is turned off, while the presence of some clouds in the sky might have decreased the solar production as well.

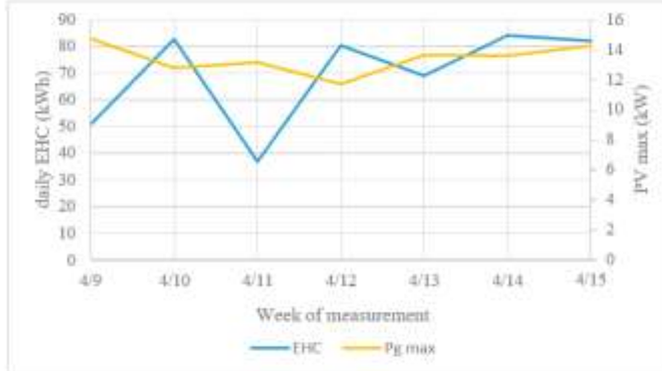

Figure 6. Daily EHC profile versus maximum PV generation.

The daily EHC profile and the maximum PV generation can be drawn, which is shown in Figure 6. These results are only significant for the performance of the grid based on PV production. Interestingly, this correlation is related to the maximum PV production, as well as the load conditions at the PCC. It is important to highlight that our results could not be tested on loading conditions because there was no exclusive measurement of the load level. Thus, the single most marked observation to emerge from the data comparison was the larger the PV production is, the smaller the energy-hosting capacity (daily hosting capacity area) will be, which can be mitigated by power quality improvement processes.

The developed model is effective at estimating system controller status over time. Annual over/under-voltage durations, on the other hand, are critical indicators in determining feeder hosting capacity. The annual over-voltage duration is projected to be 21.02 hours, which is extremely similar to the brute force result of 21.06 hours and the yearly under-voltage duration is assessed to be 18.85 hours, whereas the brute force result is 10.88 hours. The estimates indicate that the suggested model may provide a rough estimate of the duration of a system bus voltage violation.
To evaluate the performance, we use two metrics from the models. Firstly, the Mean square error (MSE) criteria, and secondly, the percentage accuracy. MSE is used by the model to conduct back-propagation, the percentage accuracy on the other hand is used to give an intuitive comparison between the calculated HC and the simulated HC. The output of the deep learning models is the calculated HC, whereas the simulated HC is the simulation result from Mendeley Data. In the test scenario, the model showed values for MSE and percentage error as 0.08 and 8% respectively

V. CONCLUSION AND FUTURE WORKS

In this work the hosting capacity approach is presented as a planning, improving, and communication tool for electrical distribution systems operating under specific uncertainties, such as power quality issues, power stability, and reliability, among others. This work has helped to conclude that the local hosting capacity should not be analyzed only statically because its dynamic nature can help operators to better deal with intermittent distributed renewable resources.

Thus, a method in the form of LSTM was used to calculate the HC in the LV distribution grid. There are two main contributions. First, this method significantly simplifies the HC analysis and calculates HC in real-time. Second, the LSTM builds a correlation between temporal and spatial sequences. Historical power system data was used in obtaining the temporal sequence.

The hosting capacity of DGs can be surpassed by grid reinforcement, reactive power regulation, or other smart technologies. It should be determined whether the proposed technique is appropriate to these expanded alternatives. While human specialists may be able to estimate the hosting capacity, the vast number of options and missing experiences in this expanded view may make it much more difficult.

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Contribution of individual authors to the creation of a scientific article (ghostwriting policy)

We confirm that all Authors equally contributed in the present research, at all stages from the formulation of the problem to the final findings and solution.

Sources of funding for research presented in a scientific article or scientific article itself

No funding was received for conducting this study.

Conflict of Interest

The authors have no conflict of interest to declare that is relevant to the content of this article.