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Review

Artificial Intelligence for Hosting Capacity Analysis: A Systematic Literature Review

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Abstract: Distribution network operators face technical and operational challenges in integrating the increasing number of distributed energy resources (DER) with the distribution network. The hosting capacity analysis quantifies the level of power quality violation on the network due to the high penetration of the DER, such as over voltage, under voltage, transformer and feeder overloading, and protection failures. Real-time monitoring of the power quality factors such as the voltage, current, angle, frequency, harmonics and overloading that would help the distribution network operators overcome the challenges created by the high penetration of the DER. In this paper, different conventional hosting capacity analysis methods have been discussed. These methods have been compared based on the network constraints, impact factors, required input data, computational efficiency, and output accuracy. The artificial intelligence approaches of the hosting capacity analysis for the real-time monitoring of distribution network parameters have also been covered in this paper. Different artificial intelligence techniques have been analysed for sustainable integration, power system optimisation, and overcoming real-time monitoring challenges of conventional hosting capacity analysis methods. An overview of the conventional hosting capacity analysis methods, artificial intelligence techniques for overcoming the challenges of distributed energy resources integration, and different impact factors affecting the real-time hosting capacity analysis has been summarised. The distribution system operators and researchers will find the review paper as an easy reference for planning and further research. Finally, it is evident that artificial intelligence techniques could be a better alternative solution for real-time estimation and forecasting of the distribution network hosting capacity considering the intermittent nature of the DER, consumer loads, and network constraints.

Keywords: artificial intelligence; machine learning; deep learning; hosting capacity; impact factors; optimisation; distributed energy resources

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1. Introduction

Greenhouse gas and climate change have become global concerns. The ever-increasing global energy demand is creating pressure on climate change. The United Nations (UN) has declared 2019 as the second warmest year and 2010–2019 as the warmest decade in history [1]. According to the UN environment programme (2022), about 80% of the global energy supply comes from fossil fuels, and the global share of electricity generated using fossil fuels is about 66%, which emits about 60% of greenhouse gas (GHG) to the environment [2]. Integrating renewable energy resources with the electricity grid could minimise the adverse effect of climate change. The share of solar and wind power increased about 10% in 2021 [3]. The contribution of renewable electricity to the global power supply reached from 12% in 2011 to 28.3% in 2021. This study shows that the renewable energy supply may increase to about 30% by 2024 [4]. To meet the zero carbon target, the electricity supply from renewable energy resources needs to increase to about 60% and 90% by 2030 and 2050, respectively [5].

Renewable energy resources have become significant contributors to energy supply in electricity distribution networks [6,7]. The high penetration of distributed energy resources with the distribution network poses technical and operational challenges for the distribution system operators (DSO) [6,8,9]. Sustainable transmission and distribution network operation maintaining the statutory power quality limits has become a significant technical and operational concern for DSO. The electricity distribution system operators should supply electric power to the consumers without violating statutory limits of the power quality [10]. Traditionally, the electric power flow maintains the unidirectional nature from the generating station to the consumers through the transmission and distribution networks [8]. The unidirectional power flow concept has changed due to the integration of distributed energy resources with the network. The variable nature of the power generation from the DER and customer load uncertainties requires real-time monitoring and data visibility for the distribution network stability. Other factors such as over voltage, under voltage, voltage unbalanced, transformer and feeder overloading, reverse power flow, network control scheme, and thermal limits of network components have emerged as significant issues for the violation of statutory limits of the power supply [10–14]. The capability to intake power from the maximum number of DER without violating the power quality limits, known as the hosting capacity, should be determined on a real-time basis for the sustainability and reliability of the network.

The hosting capacity provides policy support and network information to the DSO. The dynamic characteristics of the distribution network integrate additional power generated by the DER, maintaining the power quality within limits. Based on the network and DER characteristics, the distribution network's hosting capacity estimates the network's capability to accommodate DER while maintaining the power quality limits and without re-enforcing the network equipment. It also emphasises network reliability without further auguring the existing control configuration and infrastructure [15]. The National Renewable Energy Laboratory (NREL) has defined the hosting capacity of the distribution network as the capability to accommodate additional DER without further enhancing the control mechanism, upgrading the system components, and maintaining the safety and reliability of power supply to the consumers [16]. The Energy and Power Research Institute (EPRI) considers the hosting capacity as the output of a systematic study of the distribution network and renewable energy resources' input data based on carefully selecting a series of analytical parameters. EPRI has identified the hosting capacity as the estimation of additional DER to connect to any place on the existing network within power quality and control configurations [15]. It has emphasised the quality and granularity of data, careful selection of methods, tools, and parameters for analysis and appropriate application of the hosting capacity results. Researchers have illustrated the hosting capacity of the network as the capability to sustainably integrate the maximum amount of power from the DER within the distribution network without further augmentation of the existing resources and control systems [7,9,17,18]. The study of the hosting capacity is concerned with integrating distributed energy resources into the electric distribution networks in a technically feasible, operationally sustainable, and economically profitable manner. The analysis of the hosting capacity enables the network operators to integrate the distributed renewable energy resources [17]. It also helps to maintain network stability and DER integration reliability without further investment for upgrading network components [8,14,18,19]. The hosting capacity of the distribution network is not any static value. It depends on inputs collected from the network analysis, assumptions for the hosting capacity estimation, grid models, and impact factors [20].

The impact factors are the DER and Grid characteristics that influence the capability of the distribution network to integrate additional DER, maintaining the power quality limit and reliability of the network operation [20]. Impact factors are sometimes opposing each other. Sometimes they complement each other to enhance the DER integration capability of the network. The impact factors such as over voltage, under voltage, power loss, thermal limits, power factor, location of the renewable energy resources, harmonic distortion, real power, reactive power, control mechanism, technology, and frequency impact the capability of the network to accommodate DER in different ways. All these factors impact the approximate estimation of the distribution network capability for DER penetration [21]. Different hosting capacity analysis approaches consider the impact factors differently. Such consideration may affect the hosting capacity simulation result.

The selection of the hosting capacity analysis methods depends on present and future needs [20]. The simulation result depends upon the characteristics of the electricity network, DER, control mechanisms, transformers, conductors, and inverter technologies. The effect relies on harmonic injection, real and reactive power flow, power losses, consumer demand, and energy usage patterns. Electric Vehicles (EV) have added new dimensions for the hosting capacity analysis [22]. The complexity of the distribution grid and DER uncertainties have made the analysis more challenging. The high volume of network data, power quality indicators, and variability of DER output made the conventional hosting capacity estimation approaches insufficient to tackle operational and reliability issues of DER integration [23]. The artificial intelligence approach for the hosting capacity analysis could encompass the real-time monitoring and estimation of network variables and impact factors for calculating the hosting capacity of the network.

Both conventional and artificial intelligence approaches for the hosting capacity analysis depend on power flow analysis tools for the network input. The power flow analysis tools also assist the planning, design, and operation of the network [24]. Some power flow analysis tools are commercially available, such as PowerFactory, PSS/Sincal, PSCAD, and PSS/E. On the other hand, PandaPower, OpenDSS, PowerModelsDistribution, and OpenDSOPF are open-sourced power flow analysis tools. Different tools have their strong points and focused areas. The selection of power flow analysis tools depends on the purpose and need of the network analysis. Standard, efficient, and industry-proven tools could help to overcome network analysis challenges. Although several literature reviews on the hosting capacity analysis methods have summarised various aspects, the utilisation and impacts of artificial intelligence on hosting capacity analyses still need to be explored. They need further studies to capture its usage for system stability and network sustainability.

The information for the literature review has been gathered from different databases, including Google Scholar, ScienceDirect, and IEEE Explore. Website of other organisations such as the UN, the United Nations Environment Programme (UNEP), the International Energy Agency (IEA), the International Renewable Energy Agency (IREA), the NREL, and the EPRI has been consulted to gather the required information for this review paper. Only English-language publications have been considered for this literature review. Keywords such as artificial intelligence techniques, deep learning, DER, hosting capacity analysis, and low voltage distribution network have been considered for searching resources from databases. The most relevant research articles, review papers, conference papers, and reports have been considered for this review paper. The statistics of the article's search results could be summarised as shown in Table 1 and Figure 1.

Table 1. Publications on the Hosting Capacity Analysis of distribution network with DER.

Online Database	Period	Results
ScienceDirect	2005–2022	624
Scopus	2005–2022	504
Google Scholar	2005–2022	265
IEEE Xplore	2013–2022	42

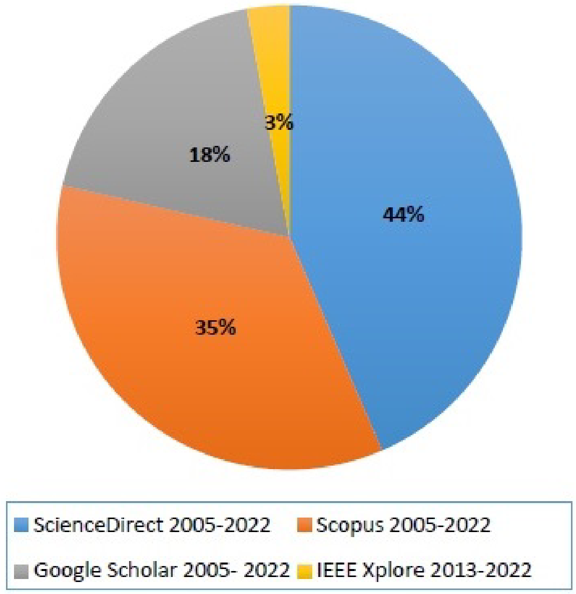

Figure 1. Graphical Representation of the Article search result.

- Contributions of the Paper
  The contributions of the literature review are as follows: (1) It has analysed the impact of Grid-based and DER impact factors on the hosting capacity estimation. The mapping of impact factors with feeder matrices has been summarised for better visibility on the relative importance of impact factors for the hosting capacity analysis; (2) The conventional hosting capacity analysis approaches were compared based on different features so that the network planners and researchers could easily select the appropriate method for the hosting capacity estimation; (3) The artificial intelligence approaches for the hosting capacity analysis have been summarised for the future direction of network planners and researchers;
- Organisation of the paper
  In this paper, the literature review and research gap has been discussed in the introduction. The impact factors have been highlighted in Section II. Section III presents the conventional and artificial intelligence technique-based hosting capacity analysis approaches. In section IV, future research directions have been discussed. Finally, the paper presents concluding remarks with guidelines for future research.

1.1. Literature Review

The hosting capacity analysis has gained much importance due to the high penetration of DER and the growing demand for renewable energy. Researchers have proposed different hosting capacity analysis methods using DER penetration scenarios based on other unknown network and DER inputs. The authors in [25] studied the impact of Volt-var and Volt-Watt settings on the hosting capacity. They investigated the PV-riched distribution network to enhance the hosting capacity using the Volt-var and Volt-Watt settings. The authors did not evaluate voltage unbalanced and DER uncertainties in the study. In [18], the researchers analysed the hosting capacity using hourly load data obtained from the rooftop PV panel output. They used MATLAB to simulate the variable output of the PV panel and load variance. The authors did not assess other renewable energy resources and network variables. Moreover, the proposed method requires millions of power flow simulations to reflect the voltage and power limits. The authors in [22] investigated the impact of EV on the distribution network. They proposed the hosting capacity optimisation model using Mixed Integer Linear Programming (MILP). The authors highlighted wind energy resources for maximising DG capacity in the study. The study did not consider the voltage unbalance of the network, real-time monitoring mechanism, and uncertainties of the power output of the renewable energy resources. In [26], authors proposed the Bayesian Optimisation (BayesOpt) to investigate the distribution network's probabilistic hosting capacity. They considered the historical data of the residential loads and DER with their uncertainties for the study. The authors in [11] considered the nodal voltage and loading of the distribution network equipment for the hosting capacity analysis using the Quasi-Static Time Series Analysis (QSTS). They analysed the grid impacts and power quality requirements through dynamic hosting capacity analysis matrices. The researchers tested the spatial Monte Carlo DPV Scenarios to obtain the impact of control schemes and results of distributed photovoltaic (DPV) power curtailment. The study only considered voltage and thermal violations as impact factors. In [17], the authors discussed the advantages, disadvantages, and impacts on the voltage and current of deterministic, stochastic, and time series hosting capacity analysis methods. They compared the output accuracy, execution time, data requirement, and uncertainties consideration of each hosting capacity analysis technique. In [27], the authors studied an integrated parallel computing algorithm-based mathematical model for the optimal solution that could provide computation effectiveness in complex scenarios. However, the proposed model is complex. It has no neutral voltage representation for unbalanced load conditions. The authors in [9] studied the optimal hosting capacity for distributed small-scale rooftop photovoltaic systems. They proposed the Monte Carlo method using a stochastic analysis approach to estimate the hosting capacity. The authors in [11] studied the impact of voltage violation at the customer end and thermal violation at network components on the dynamic distributed photovoltaic hosting capacity using QSTS simulation. The authors investigated the severity of the parameters' violation period on hosting capacity by employing the dynamic DPV hosting capacity matrices. The proposed study did not cover a real-time hosting capacity analysis of the distribution network. The authors in [10] proposed the stochastic-based photovoltaic hosting capacity analysis method for the hosting capacity analysis. The probabilistic hosting capacity of the distribution network was studied in [28] using multi-parametric programming (MPP). The study used the optimal grid model and considered the feasible and infeasible optimal power flow (OPF) instances. The proposed method reduced the computational burden of many OPF instances. However, it could not measure the real-time scenarios of the DER and distribution network parameters.

In [29], the authors proposed various tariff schemes such as time-of-use (TOU), net metering, and distribution locational marginal pricing (DLMP) for EV charging to investigate the impact on the residential distribution network's hosting capacity. The authors considered the impact of the flexible load created by EV. However, the authors did not cover other factors such as voltage unbalance, network constraints, and DER uncertainties. In [30], the authors studied the distribution network to maximise the hosting capacity with a high penetration of DER. It considered the technical and economic impact factors as objective functions. They proposed the stochastic multi-objective optimisation model for the hosting capacity maximisation with wind power sources. The proposed model emphasises reducing the renewable energy production and operational cost. It did not include the renewable energy resource (RES) uncertainties, voltage unbalance, and real-time monitoring of the power quality supplied to the consumers. In [31], the authors considered the balancing, profile, and grid-related cost as the primary concern from an economic perspective. They proposed an AI-based economic model to reduce the integration cost substantially. The author studied the deep-learning-based application, technical data, and deployment architecture in [32]. They considered data availability to be a significant constraint for model testing and development purposes. In [11], the grid impacts and penetration of photovoltaic energy resources have been studied through power flow analysis by the QSTS method. The continuation power flow (CPF) algorithm was proposed in [33] for determining the hosting capacity with distributed energy resources. In the study, the authors considered the DER outage due to the abrupt disturbance or voltage instability for the generator sudden ramping. The proposed method only considered the under-voltage criteria and ignored other factors. In [34], the authors introduced the random forests and firefly algorithm (RFs-FFA)-based hybrid model to predict the hourly global solar radiation more accurately. They tested the proposed prediction model using various statistical tools and techniques for the external and internal validation of the proposed prediction model. The authors in [35] studied the deep-learning-based Spatial–Temporal long short-term memory (ST-LSTM) on the IEEE 34-bus, 123-bus feeders, and 12.47 kV 9 km-long Arizona utility feeders to validate the proposed method for hosting capacity analysis. The authors incorporated spatial and temporal correlations for predicting the hosting capacity at each distribution network node in the study. However, the study did not include the voltage sensitivity data.

The authors in [36] proposed the DGHost approximation technique by applying the k-Nearest Neighbour Algorithm (k-NN). They investigated the consequences of the current generated from small-scale renewable energy resources such as rooftop solar systems on the hosting capacity of the low-voltage distribution network. The proposed method needs the minimum network data for calculating the hosting capacity. The authors also used cross-validation techniques to optimise the system and the accuracy of the result. The study only considered the small-scale inverter-connected DG and low-voltage distribution systems. The proposed DGHost methods require the complete model information of the network, such as network connectivity and equipment parameters, which makes it challenging to implement. In [37], the authors tested the machine-learning-based static multi-agent reinforcement learning (MARL) algorithm to maximise the distribution network's hosting capacity and voltage flexibility. The study covered converter-interfaced generators (CIGs) such as PV panels, wind generators, micro-turbines, and fuel cells using the secondary voltage control mechanism. The authors validated the proposed method on the modified IEEE 34-bus test feeder containing CIG for validation. The authors in [38] investigated the algorithm of deep learning-based k-means clustering based Convolutional Neural Networks' and Long Short-Term Memory (kCNN-LSTM). The authors tested the model using granular data for 15 minutes of energy consumption to forecast the energy demand accurately. In [39], the authors examined the support vector machine (SVM) algorithm to classify the low voltage distribution grid feeders based on the sample data. The proposed model depends on the input data accuracy to estimate the penetration level of the grid based on the node voltages and loads. The study should have included other factors of the network and DER. The researchers in [40] proposed the artificial intelligence (AI) methods for variable renewable energy (VRE) resources with the distribution network, considering the economic and business viability. The study highlighted the financial aspects of VRE integration but overlooked the uncertainties of the network and DER. In [13], the authors proposed a Spatio-temporal Probabilistic Voltage Sensitivity Analysis (ST-PVSA) framework to calculate the hosting capacity at a particular distribution network node with DER. The study considered voltage unbalances, random behaviour of the photovoltaic resources distributed in a random location, and distribution network parameters. The proposed method should have covered voltage and power limits' violation analysis over a short period using the load and photovoltaic (PV) system time series data.

Research Gap

The modern electricity network is considered the most complex system for the versatility of grid interconnections, equipment-wide points, and operating characteristics. The high penetration of residential and commercial renewable energy resources has complicated the technical issues of the distribution networks for the network operators' or at the customers' end [41]. Accurate estimation of the network capability to withstand the additional injection of power generated from the DER [14] is the crucial factor for hosting capacity analysis. The sustainable operation of the distribution network with a high penetration of DER depends on the network's real-time visibility and data transparency [41]. Proper consideration of input assumptions and precise selection of impact factors [20] affect the output of the hosting capacity of the distribution network and sustainable integration of renewable energy resources.

The consumer load uncertainty, DER characteristics, inverter technology, and network control mechanism have increased the non-linearity in the network analysis [42].

The hosting capacity analysis depends on the input data, impact factors, uncertainties, and objective functions. Related works have categorised the hosting capacity analysis studies as deterministic, stochastic, streamlined, and iterative. The deterministic method is a model-based approach that determines a single output based on known inputs. This method does not consider the time-series variations of the input data. The stochastic method considers the distribution network and DER uncertainties. The probabilistic approach of the hosting capacity analysis considers the uncertainties of the network and DER to estimate the hosting capacity of the distribution network. Both deterministic and stochastic methods fail to cover the time-series effect of network and DER uncertainties. The streamlined and iterative methods consider the time-series effect of the input data for calculating the hosting capacity of the distribution network to accommodate additional DER without further infrastructure upgradation. The streamlined approach depends on a series of mathematical equations and complex algorithms. The iterative method gradually increases the DER penetration level and calculates the influences of different impact factors. It creates a substantial computational burden for the hosting capacity analysis.

None of the above hosting capacity analysis methods covers the real-time monitoring of the network and DER parameters to accommodate the time-varying effect. The supervised and unsupervised dynamic hosting capacity analysis methods consider the probabilistic nature of the network and DER data. These methods conduct an extensive power flow analysis based on a network model for obtaining the hosting capacity of the distribution network [35]. The researchers have proposed different AI techniques to overcome the computational burden of numerous power flow analysis scenarios, reduce computation time, increase efficiency, and enhance result accuracy. The distributed energy resources are intermittent in nature [17]. The hosting capacity analysis requires real-time network data monitoring, accurate forecasting of load demand, and DER power output.

Artificial intelligence algorithms are flexible and efficient. They could capture the non-linearity of the hosting capacity analysis of the distribution network with the high penetration of DER. Researchers have studied different artificial intelligence algorithms such as Multi-Parametric Programming (MPP) OPF [28], the random forests technique and firefly algorithm [34], Spatial-Temporal LSTM (ST-LSTM) [35], Multi-Agent Reinforcement Learning (MARL) [37], kCNN-LSTM [38], Support Vector Machines (SVM) [39], long short-term memory (LSTM) [43], Improved Sine Cosine Optimisation Algorithm-based LSTM (ISCOA-LSTM) [44], One-step Secant Backpropagation Neural Network (OSSB-NN) and BFGS Quasi-Newton Backpropagation (BFGS-QNB) [45], Policy Function Approximation (PFA) [46], a novel combination of Teaching–Learning-based Optimisation (TLBO) and Honeybee-Mating Optimisation (HBMO) algorithms [47], and the random forests technique [48] to explore different aspects of the hosting capacity in real-time scenarios. Most studies highlighted other prediction models. Some studies covered analysis, optimisation, and distribution network hosting capacity enhancement techniques. Researchers in [38,44] studied the consumption and demand forecasting of the distribution network. In [43], the authors focused on the prediction of the peak demand of the distribution zone. The authors in [45] focused on forecasting the short-term energy and load demand. The photovoltaic current output prediction technique and PV output have been analysed in [48,49]. The authors in [28,35,37,47,50] studied the hosting capacity optimisation of the distribution network. In [35], the authors investigated the deep-learning-based Spatial–Temporal LSTM to predict the real-time hosting capacity of each distribution network feeder. The authors analysed voltage magnitude, voltage angles, load profiles, and PV profiles. In [37], the authors proposed the multi-agent reinforcement learning algorithm to maximise the distribution network's hosting capacity and voltage flexibility. In [40], the authors studied the VRE integration cost for cost optimisation. Distribution grid classification for hosting capacity analysis has been focused in [39], and the impact of the PV-battery system on the distribution network has been studied in [46]. Few studies have covered the real-time monitoring of the distribution network and DER uncertainties for optimal network hosting capacity to accommodate the maximum power from renewable energy resources. In [23], the authors proposed Multi-Objective Cat Swarm Optimisation (MO-CSO) to study the uncertainties and DER penetration level. They have verified the algorithm using the backward-forward sweep power flow on an unbalanced IEEE 34-bus radial system network. The authors did not cover the demand response in their study.

2. Impact Factors

Impact factors are the inputs and assumptions that determine the power system network's boundary values to assess the hosting capacity of the distribution network [20]. The network capability to integrate DER depends upon various impact factors. Different hosting capacity analysis methods consider multiple factors to analyse the network capacity to integrate DER without violating the power quality boundaries [51]. The obtained result, the accuracy and complexity of the hosting capacity analysis framework depend on the careful selection of the impact factors. The more impact factors considered, the more complexity arises for analysis. The impact factors could be categorised based on the network and DER characteristics, namely Grid-based impact factors and DER impact factors.

2.1. Grid-Based Impact Factors

The grid-based impact factors determine the current circumstances of the distribution network to integrate additional power from the DER. It also defines the present state of the network for calculating the hosting capacity. Most factors influence the voltage levels of the power network. Other factors affect grid components' impedance, reliability, protection, and thermal issues. The importance of the impact factors depends upon their influence on network issues. The grid-based impact factors could be summarised as in Table 2.

Table 2. Grid-based Impact Factors.

Impact Factors	Description
Network Configuration	The distribution feeder model and configuration are the primary concern for hosting capacity analysis. Each feeder is unique for operation and changes its characteristics based on the orientation and configuration [52]. The grid's static and dynamic configuration dramatically affects the distribution network's hosting capacity. Each feeder has a distinctive hosting capacity due to its unique characteristics. The network topology, control equipment location, transformer location, cable characteristics, the active and reactive power control mechanism, and power factor significantly affect the network hosting capacity [53].
Source Impedance of Feeder Model	The feeder model impacts the hosting capacity with renewable energy resources. Generally, the distribution feeders are designed to be radial in nature [20]. Hosting capacity analysis considers the existing distribution network model and equipment data. Operators maintain operational flexibility to cut off any feeder section for maintenance or other operational purposes. Such activities affect the voltage profile, transformer loading, and thermal limits of the conductors and other components of the network. The hosting capacity depends upon operational flexibility. The normal 'as designed and the abnormal re-configured operating condition of the feeders [20] affect the distributed energy resources penetration level.
Connected DER	The location, technology, amount, type, and control mechanism of the DER affect the voltage profile, thermal limits, and control system of the power network [7,10,14]. The impact of connected DER should be considered for hosting capacity analysis.
Connected Load	The nature, location, and amount of connected load affect the distribution feeders' voltage profile, protection analysis, and thermal limit. Hosting capacity analysis highly depends on the nature of the connected loads [54]
Thermal Limits	The connected DER impact the apparent power level in the electricity network. It determines the maximum allowable apparent power in the network branch and depends upon the network assets and their specification, such as transformers, control equipment, and conductors [55]. The hosting capacity of any branch should satisfy the thermal limits of the network components.

Table 2. *Cont.*

Impact Factors	Description
Control Scheme	The active and enhanced control mechanism affects the network's hosting capacity to integrate more DER [51]. The autonomous and managed control system with adequate data, communication system and functionality determine the boundary conditions of hosting capacity to accommodate more DER power injection into the distribution network [56].
Time	Time reflects the impact of the various grid and DER factors. A realistic scenario could be generated using the time-varying analysis to integrate more DER with the distribution network [14].
Voltage Regulation	The voltage regulating equipment in the distribution network prevents the under and over-voltage due to abrupt load changes or power output uncertainties due to the distributed energy resources. The voltage profile generated from the voltage regulating devices should be considered for hosting capacity analysis [52]. The DER output uncertainties influence the distribution network's voltage at common connection points. The real and reactive power injected from the distributed energy resources also affects the voltage level of the network [55]. At any node of the network, the voltage level V_{α} requires to be maintained within the permissible limit V_{min} and V_{max} for sustainable and reliable power supply to the consumers. Power quality depends upon the voltage profile generated by the voltage-regulating devices. The uncertainty of the DER output and the abrupt change of the consumer's load may deteriorate the distribution network's voltage profile. Voltage regulating assets keep the voltage level within the allowable limits and prevent under-voltage and over-voltage problems in the power network [56]. Thus, the voltage profile provides the necessary information to the network's hosting capacity enhancement to incorporate more power into the network. Deploying capacitor banks, additional control mechanisms, adjustment of voltage regulating equipment, and setting the operating bandwidth of these assets help to flatten the voltage profile that enhances the hosting capacity of the network [57].
Transmission and Distribution network integration	A recent study in [53] found that the flexibility in network topology significantly increases the hosting capacity of the network. Based on the case study on the modified 33-Bus system, the authors in [53] observed about 37% increase in hosting capacity deploying power factor control mechanism of DER and voltage control of distribution network through OLTC. The high penetration of DER in the distribution network causes transmission network planning challenges for integration with the distribution network. The high power injection into the distribution network may create voltage unbalance, bi-directional power flow [58], the difference in phase angle [59], fault current enhancement, frequency instability, and network losses. Conventional power flow analysis assumes the transmission line as a slack bus and overlooks the impact of DER constraints. Large-scale DER penetration has caused voltage instability, bi-directional power flow and integration complexity for the transmission network planners [58]. The effectiveness of coordinated transmission and distribution network integration has been investigated in [59]. The study revealed that the high penetration of DER at the substation end of the distribution network could increase the over-voltage problem, fault current, and phase unbalance, especially during mid-day. In [60], the authors studied the impact of energy storage on hosting capacity and transmission integration problems. They have found that small-scale energy storage devices could substitute or complement the line investment considering the penetration level, location of the energy storage system and coordination of the network integration. In [61], the authors analysed the risks associated with the reactive power control of DER. The study found that reactive power control could reduce the transmission-distribution network integration and operational risks related to the high penetration of DER.

2.2. DER Impact Factors

The characteristics of the DER, such as the location, technology, power output, converter technology, panel efficiency, and weather pattern, impact the distribution network components' voltage, loading, and thermal limits. The DER-based impact factors can be summarised as in Table 3.

Table 3. DER-based Impact Factors.

Impact Factors	Description
DER Location	DER location is the most critical impact factor on the voltage profile and thermal limits for the distribution network's hosting capacity estimation [9,20,52]. DER could be connected at a single point or multi-points along the distribution network feeders. Single-site and multi-site scenarios should be considered for estimating the feeder hosting capacity. The location of the DER concerning the distribution transformer affects the voltage profile of the feeders. DER connected near the substation transformer's end may raise the voltage level. There are possibilities of voltage drop and thermal limit violation when the DER are connected at the farthest end of the feeders. The hosting capacity should also be analysed considering the upstream and downstream DER locations [52]. The DER could be connected at multi-locations distributed along the feeders. In each case, separate scenarios should be analysed to obtain the actual hosting capacity of the network.
DER Technology	The hosting capacity of the distribution network depends on the technology used for DER. The DER technology could define its characteristics that may affect the hosting capacity of the network [52]. The fixed output and variable output DER have different impacts on the network's integration capability. The connected inverters could control the network's active and reactive power feed, which may influence the hosting capacity. The DER's total output period should correlate with other grid factors to determine network integration capability. The DER interface modality and technology used for real and reactive power control mechanisms through connected inverters also impact the hosting capacity.
DER Aggregation	The connected DER affect the future connection request from the consumers. The hosting capacity analysis should consider aggregating the existing and future renewable resources. The network planner and distribution system operators should carefully consider the new DER connection request and forecasted amount of DER for network stability and reliability to calculate the feeder hosting capacity.
Other DER Factors	The efficiency of the distributed energy resources, manufacturing technology, and plant topology also impact the hosting capacity. The power output also depends on weather patterns and the location of renewable energy resources. The photovoltaic panel orientation could also impact the network's hosting capacity.

All grid and DER-based impact factors highly affect over-voltage, under-voltage, and regulator voltage deviation. The grid's source impedance and voltage profile slightly affect the network's reverse power flow and thermal ratings. An automated control scheme may overestimate the hosting capacity of the network. Active and reactive power control schemes may increase the DER integrated with the network. The DER-based impact factors such as DER location, technology, and inverter settings highly influence the number of DER to be connected with the network. The feeder matrices have been mapped with the Grid and DER-based impact factors in Table 4.

Table 4 clearly shows that the Voltage profile is highly related to all the grid-based and DER-based impact factors. Over-voltage, under-voltage, and voltage deviation originating from the voltage regulation scheme are deeply related to all the other impact factors. Feeder cable, substation transformer, connected DER, and load impedance directly affect the voltage profile and may increase network loss, causing thermal violation problems in the network. The amount, location, and variability of the load aggravate the voltage regulation scheme, making it more challenging. It may cause over-voltage during high generation and low demand periods such as mid-day in sunny weather. The network flexibility to accommodate or curtailment of DER power injection, load management scheme, and coordinated protection scheme improve the network operational reliability and power quality to the consumers. DER location and inverter technology affect the distribution network's voltage profile and thermal ratings. Real and reactive power injection through the DER connected inverter helps to manage the distribution network's voltage profile and power factor management.

Table 4. Impact Factors Mapped with Feeder Matrices [52].

Feeder Matrices	Grid-Based Impact Factors						Other Impact Factors				
	Network Configuration	**Source Impedance**	**Voltage Regulation**	**Connected DER**	**Connected Load**	**Control Scheme**	**Time**	**DER Location**	**DER Technology**	**DER Aggregation**	**DER Portfolio**
Over Voltage	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Under Voltage	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regulator Voltage Deviation	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Voltage Deviation	Yes	Yes	X	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Reverse Power Flow	Yes	X	X	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Operational Flexibility	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Thermal Ratings	Yes	–	–	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Protection Coordination	Yes	Yes	Yes	Yes	Yes	–	–	Yes	–	Yes	Yes

Careful selection of grid and DER-based impact factors determines the accuracy of the hosting capacity result and computational complexity. Considering more impact factors increases the computational burden and required time. The feeder matrices characterise the influence of impact factors. It provides information and visibility on the relative importance of impact factors for the hosting capacity analysis. From the above tables, it is clear that all network issues are not equally affected by all impact factors.

2.3. Electrical Demand and Flexibility of Different Energy Sectors

Generally, the power system is designed to meet the aggregated maximum demand. The power generation should be sufficient to supply consumer loads at any time. Distributed energy resources have caused excess generation that exceeds the aggregated demand. It causes technical and economic issues for the DSO. The demand-side management using incentive or price mechanisms [62] could minimise the problems arising from the distributed energy resources integrated with the distribution network. The demand side response positively correlates with the distribution network's hosting capacity. The voltage profile violation due to the high penetration of distributed energy resources could be mitigated through coordinated demand management schemes. This would generate both technical and economic benefits for the DSO and consumers. A Residential Demand Response (RDR) could reduce power quality violations due to a low demand and a high DER generation period.

To increase PV hosting capacity in the distribution network, the RDR-based demand management structure was analysed in [63]. In the proposed structure, the researchers shifted the residential loads for better utilisation of distribution network resources based on cost, revenue, and consumer discomfort level to observe the effect on hosting capacity. In the case study on the modified IEEE 15-bus system, 33.6% more hosting capacity has been observed deploying the proposed scheme. In [64], the authors investigated the impact of the variable load of EV on the hosting capacity of the distribution system. They evaluated the permissible EV penetration level on the distribution network using the demand response-based method on the RBTS, IEEE-RTS, and IEEE-33 Bus System. The study found that the driver's behaviour, EV charging location, time, and duration negatively impact the penetration level in the distribution network and could be mitigated using the interruptible/curtailable load-based DR method. The Energy Storage (ES) and Demand Side Response (DSR) have been investigated in [65], considering the ES and DSR as optimisation constraints in the nonlinear multi-period optimal power flow (OPF) of the distribution network. A case study based on the optimisation algorithm on an 11 KV distribution network with 38 buses and 37 branches found that ES and DSR are very effective in optimising the existing network assets, minimising network losses, enhancing supply reliability, and increasing supply power quality. High generation and low demand in a distribution network with a high penetration of PV, especially during sunny weather, could generate high voltage deviation [66] in the network. Low generation and increased demand also cause low voltage profiles and high line losses at the distribution feeders. In [67], the authors compared the distribution network's hosting capacity and loading effect. On a 20 KV radial distribution system with four feeders, 33 nodes and 32 branches, the hosting capacity was observed to be up to 70.40%, applying a reactive power control mechanism. The power generation from the distributed resources and variability of the load has been studied in [68] to investigate the impact on the hosting capacity. The study observed up to 85.7% of the hosting capacity. A distributed load management scheme has been proposed in [69] to enhance the hosting capacity of the distribution network through domestic load variation. They found that the load management could increase PV penetration, decrease PV curtailment, and improve power quality.

3. Hosting Capacity Calculation Approaches

The green and renewable energy resources, from bulk to small photovoltaic sources, are distributed over the transmission and distribution network. The technical parameters and the operational performance of the distribution network change with the penetration level of the DER [11,14,17]. It causes an unbalance of allowable voltage levels to the customer ends, thermal overloading to the transmission and distribution lines, transformer overloading, protection disruption, harmonic distortion, and excessive losses in the distribution network [8]. The impact level depends upon various factors such as the location of the DER, amount of electricity injected, electricity generation pattern, active and reactive power control mechanism, network topology, control equipment, and power factor [9,22].

The hosting capacity analysis begins with creating the network model in model-based approaches (Figure 2). The network performance parameters such as voltage variation, power quality, losses, and thermal overloading are set for checking the parameters' violation for DER penetration. The hosting capacity analysis algorithm is set based on the hosting capacity analysis method. The set algorithm examines the performance parameters' violation scenarios. The DER penetration level is increased until the performance indices' violation occurs. The highest level of DER penetration at which the performance indices' violation occurs is determined as the hosting capacity.

The hosting capacity of the network depends on the network and DER impact factors. It is measured based on the highest level of the distributed energy resources that could be sustainably integrated with the distribution network without further augmentation of the existing network resources maintaining the power quality within the statutory limits [10,14,26,70]. In [12], the hosting capacity of a network has been expressed as the aggregated result of the added photovoltaic energy resources that can be connected within the allowable operational limits. The mathematical formulation of the hosting capacity of feeder N could be expressed as,

$$HC_N = \sum_{f \in_N} \cdot HC_f \tag{1}$$

where Hosting Capacity for feeder f is

$$HC_f = \sum_{P \in p_f} P \ \ with\ respect\ to\ |p_f| \leq |D_f|. \tag{2}$$

Here, p_f is the set of the new photovoltaic sources connected to feeder f; and D_f is the set of consumers connected to the low-voltage feeder.

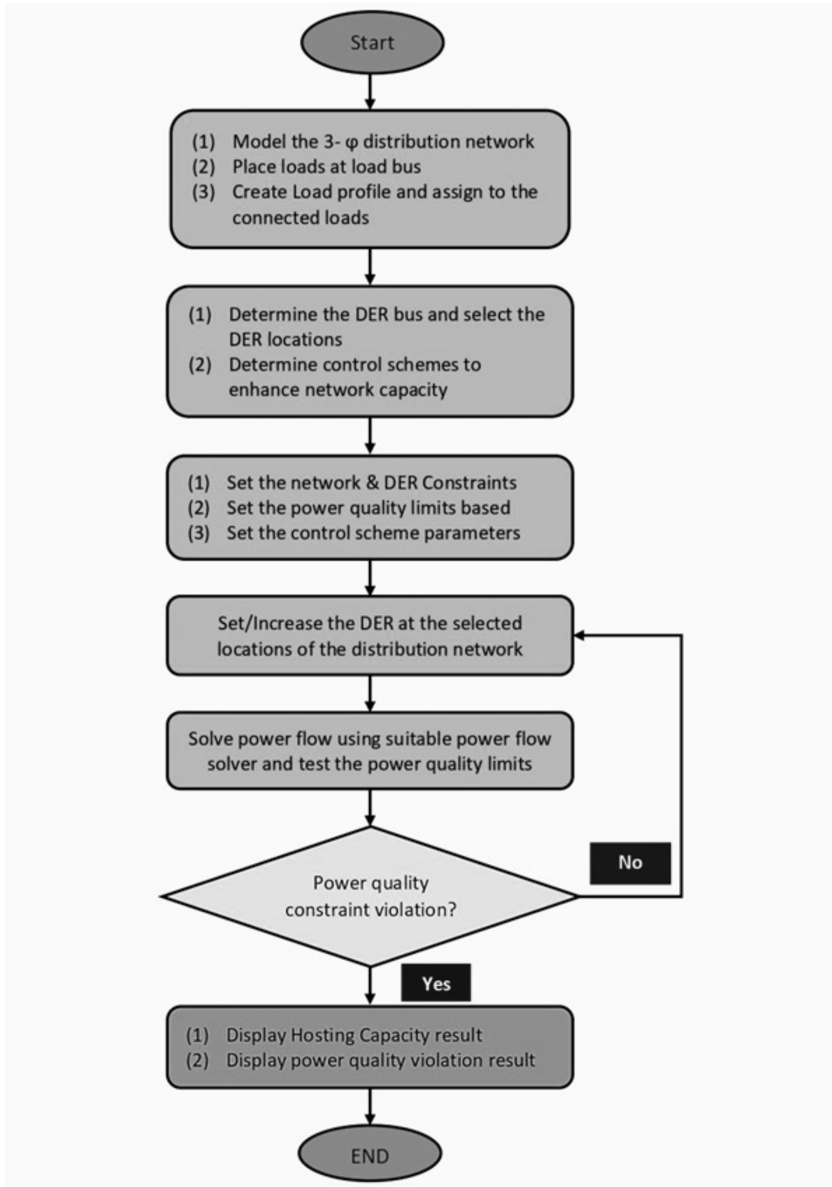

Figure 2. Hosting Capacity Analysis Flow Diagram.

The choice of hosting capacity analysis methods depends on considering the number of uncertainties of the networks and distributed energy resources, grid performance indices, available data, power consumption pattern, and the network model [12]. It also depends on the objectives of the particular study [71]. The accuracy of the results and the impact factors considered are other essential factors for selecting hosting capacity analysis methods. The choice among the methods may differ based on the available input data, time, uncertainties, network model, and network complexity [14]. Feeder characteristics, technologies of the distributed energy resources, energy policies, operational and economic considerations, reliability, and functionality of simulation results may also affect the choice of the hosting capacity analysis methodology [72].

The hosting capacity analysis could be broadly categorised as conventional and data-driven methods. The conventional hosting capacity analysis methods depend on different types of power flow simulation. The data-driven methods rely on the time-series network and DER data. The hosting capacity analysis methods are shown in Figure 3.

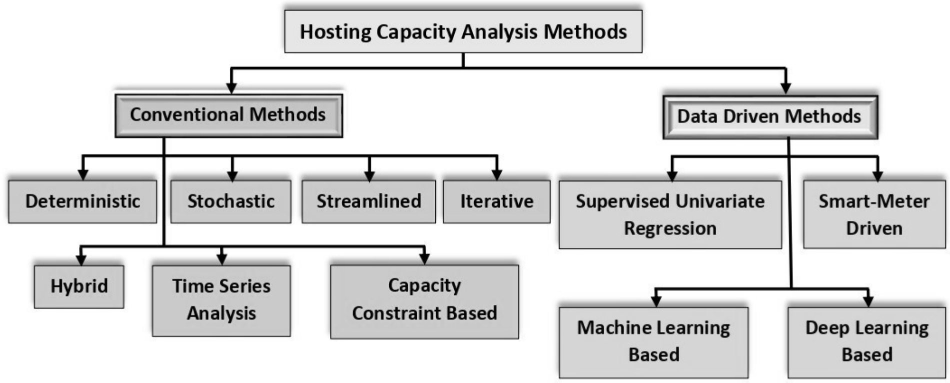

Figure 3. Hosting Capacity Analysis Methodologies.

The published articles have been searched from databases, including Google Scholar, Scopus, ScienceDirect, and IEEE Xplore for up-to-date information on the hosting capacity analysis methods. The related articles have been selected based on keywords such as conventional hosting capacity analysis methods, the hosting capacity enhancement, the hosting capacity analysis with DER, and individual methods' names. Various websites of research organisations such as EPRI and NREL, and organisations such as the Australian Renewable Energy Agency (ARENA), UNEP, IEA, and IREA have been consulted for searching relevant information. The reference list has included all relevant articles, reports, and websites that has been consulted for this paper.

3.1. Conventional Approaches

Based on the network characteristics and distributed energy resources integration technical issues, the Deterministic, Stochastic, Streamlined, Iterative, and Hybrid methods are mainly used for the hosting capacity analysis of the distribution networks [71]. The methodology for the hosting capacity analysis is governed by different technical assumptions that may affect the accuracy and functionality of the results [72].

3.1.1. Deterministic Method

The deterministic method is a fundamental hosting capacity analysis method for evaluating the impact of distributed energy resources on the distribution network. In this method, all the connected DERs are considered at a time. It calculates the single output considering the total output of all connected DER [17]. The DER output, location, characteristics, and consumer load demand are taken as known data for calculating the hosting capacity [12,14,17]. The hosting capacity is calculated through the power flow simulation, harmonic analysis, and unbalanced power flow simulation [17]. The network model, line parameters, voltage profile, network equipment data, inverter technology, and consumers' power demand information are required as input data for the power flow simulation. The analytical and rule-based analysis could also be adopted for the fixed generation and time-series-based deterministic hosting capacity analysis method [14]. In the fixed generation analysis process, all photovoltaic sources are considered to generate a fixed amount of power at all times. In the time-series analysis process, the time variation of the output of photovoltaic sources is considered for the hosting capacity analysis [17].

Uncertainties of distributed energy resources, production uncertainty, and power consumption variability are not considered in the deterministic method [12,14]. It is regarded as the most simplistic method of the hosting capacity analysis with simple mathematical calculations [14], less computation burden, and speedy output. This method considers the worst-case scenarios that affect the precision of the simulation result [70]. The output also depends on the availability and accuracy of analysis data [17]. It tends to overestimate and miscalculate the network hosting capacity. The deterministic hosting capacity analysis method could not analyse the realistic scenarios of the distribution network. This method did not consider the uncertainties of the network, customer load, and DER characteristics. Therefore, it could not reflect the integration impact of the high penetration of the distributed energy resources with the medium and low voltage distribution network [12].

- Relevant studies on Deterministic Method
  The deterministic method for the hosting capacity analysis has been studied in [36,73–79]. In [36], the k-nearest neighbour regression algorithm (k-NN) has been used for DG hosting capacity forecasting. The study has investigated the impact of the line impedance, transformer short circuit impedance, and feeder length on voltage fluctuation for the high penetration of the distributed Generators. The authors in [73] studied the voltage unbalance through simulation of the direct voltage unbalance of the distributed network, consisting of 5 KW inverters in Swedish networks and 3.0 KW, 3.7 KW, and 4.6 KW inverters installed in German networks. The penetration level was studied using the location and phase position of the PV inverters. The impact of harmonics on power quality, thereby limiting the hosting capacity of the distribution network, has been investigated in [74]. The authors investigated the impact of harmonic voltage, power factor, load, and voltage regulation equipment on the magnitude of the harmonic voltage. The study conducted in [75] revealed that transformer overloading might occur at medium voltage distribution networks due to the high penetration of distributed energy resources. The authors studied the impact of solar potential and grid integration considering the voltage band, line loading, and transformer loading of the distribution network. Considering the PV utilisation factor as a driving parameter, they implemented the forward, backward and even PV increase on the analysis model to analyse the hosting capacity of each node of the distribution feeder. Linearised power flow model has been investigated in [76] for analysing the impact on voltage magnitude, losses, real and reactive power injection, and feeder capacity of the distribution network. The authors considered the DER output, consumer demand, and real and reactive power load as input for the simulation. In [77], the hosting capacity has been studied using the voltage profile through power flow simulation using the PSCAD. The voltage fluctuation issues due to the penetration of photovoltaic energy resources have been studied using the feeder impedance, transformer parameters, and transformer short circuit resistance. In [78], the authors investigated the impact of the real and reactive power losses, voltage unbalance, voltage magnitude, and fault on network hosting capacity. They perform the power flow analysis and short circuit analysis for the study. The authors validate their findings in the IEEE 34 Node distribution test feeder using the DIgSILENT power factory software. In [79], the power flow analysis was used to calculate the impact of reactive power, power factor, and power curtailment on the hosting capacity in the 73-node 33 kV distribution system located in the town of Al-Qatraneh in Jordan. Different studies have considered different impact factors, input variables, and simulation processes for estimating the hosting capacity of the distribution network using the deterministic method as illustrated in Table 5.
- Impact Factors and Required Data
  The study has been conducted on different impact factors with different input data types. The objective functions and expected output also differ from each other. Voltage, power, power loss, real and reactive power, network data, load, and control parameters have been used as impact factors for hosting capacity analysis. Moreover, the output of the study differs in input data and its resolution. Consumer load demand, DER output, line parameters, location, power factors, power loss, transformer data, feeder impedance, and line geometry have been used as input data in studies for hosting capacity analysis by the deterministic method. In [36], phase imbalance and DG penetration level have been considered as the impact factors. The authors conduct the power flow simulation using the low-voltage network, overhead line geometry, and DER location as input data to determine the network hosting capacity. Negative sequence voltage and voltage unbalance have been taken as impact factors considering

the location, phase allocation of the PV inverters, tilt angles of the PV arrays and electric vehicle chargers as input data in [73]. Direct harmonic voltage and magnitude calculation simulation have been studied considering harmonic voltage and voltage rise as impact factors, taking the harmonic injection of the current, power factor, and RMS magnitude of the nodal voltage and current injection as input parameters in [74]. In [75], the authors analysed the impact of the line and transformer loading, and voltage limit on the hosting capacity of the distribution network. The study revealed that the even distribution of DER along the feeder has a positive impact on the hosting capacity. It also identified transformer overloading as the significant limiting factor for the feeder's capability to integrate more PVs. In [77], a power flow simulation has been conducted for the hosting capacity calculation using the voltage magnitude profile as the impact factor, feeder impedance, transformer parameter, transformer short circuit resistance, and feeder length as input parameters. The authors in [78] conducted the power flow and short circuit analysis simulation considering the power loss, voltage magnitude, and voltage unbalance as impact factors for analysing the hosting capacity. The study used the real and reactive power losses, voltage profile, phase imbalance, fault level of the distribution system, and consumer's load demand as input data. The researchers validate the research findings in the IEEE 34 Node distribution test feeder. In [79], the voltage level, DER output, and overload of transmission lines have been used as impact factors for conducting the power flow simulation. They considered the consumer's load demand, PV output, power feedback to the transformer, and reactive power control as input data for the study.

Table 5. Impact factor, input, and simulation process for deterministic method.

Impact Factors	Input	Analysis Method	Reference
Phase imbalance, DG penetration level	LV network data, overhead line geometry, DER location	Power flow Simulation	[36]
Negative sequence voltage, Voltage unbalance	Location, phase allocation of the PVIs, tilt angles, electric vehicle chargers (EVCs)	Voltage unbalance simulation	[73]
Harmonic voltage, voltage rise	Harmonic injection, power factor, RMS magnitude (nodal voltage)	Direct harmonic voltage and magnitude calculation simulations	[74]
Line loading, transformer loading, voltage limits	PV utilisation factor, grid data	Power flow simulation	[75]
Voltage magnitude, Losses, Real and reactive power injection, Feeder capacity	DER output, power demand, real and reactive load, active power loss sensitivity factor	Linearised power flow model	[76]
Voltage magnitude profile	Feeder impedance, transformer parameter, transformer short circuit resistance, feeder length	Power flow simulation	[77]
Losses, voltage magnitude and unbalance	Losses (real and reactive), voltage profile, phase imbalance, and fault level, load demand	Power flow and short circuit analysis simulations	[78]
Voltage, power, overload of transmission lines	Customer load, PV output, Power feedback to the transformer, Reactive power control	Power flow simulation	[79]

The deterministic method is the simplest method of hosting capacity analysis. Considering the DER output as a known value, this method gradually increases the penetration level to observe the power quality violation. It does not consider network and DER uncertainties. Based on the worst-case scenarios, it estimates the network's hosting capacity result through power flow simulation. It is the simplest method for getting a general overview of the network capability with a simple mathematical formulation and less time-consuming simulation. This method could not generate real network and DER scenarios, and often over-estimate the network capability; therefore, it is inappropriate for the practical application of complex networks and the real-time monitoring of DER for integrating with the distribution network.

3.1.2. Stochastic Method

The stochastic method considers the existing distribution network model along with probabilistic uncertainties [17]. It includes the uncertainties of size, location, and output of the distributed energy resources in the stochastic analysis for calculating the hosting capacity of the distribution network [9,13,40]. This method gradually increases the DER penetration level at different distribution network locations to observe the adverse effects on other network parameters. It also generates different scenarios to estimate the maximum allowable limits of the network to integrate the DER output without violating the acceptable limits of the power supply parameters [71]. The stochastic method also helps to measure the probable impacts at various locations and sizes of future impacts.

In the stochastic method, hundreds of simulation scenarios are generated based on the uncertainties considered to measure the hosting capacity of the network [10]. It involves complex mathematical calculations and intensive computational efforts that require significant execution time [17]. The repetitive problems occur due to generating numerous scenarios [10]. The level of the simulation complexity depends on the number of uncertainties included in the study [17]. The computation complexity, simulation time, and memory usage increase with the number of uncertain variables of the distribution network and distributed energy resources. The uncertainties considered and the complexity of the calculation methods negatively affect the accuracy of the hosting capacity result [10].

Researchers have proposed improvement techniques to enhance the result's accuracy and overcome repetitive problems during simulation. Different improvement techniques such as Improved Stochastic Method [10], Bayesian Optimisation (BayesOpt) [26], Multi-parametric Programming (MPP) [28], Multi-Objective Optimisation Model [30], and Stochastic Analytic-probabilistic Methodology [70] have been discussed in the various literature. In [10], the authors studied the improved stochastic analysis method for the hosting capacity assessment with photovoltaic energy resources. The study introduced a quick sorting algorithm to overcome the errors during the simulation process due to the repetitive photovoltaic deployment. The study analysed voltage quality such as overvoltage, voltage deviation, and voltage imbalance as primary system performance indices for PV penetration. It used MATLAB and OpenDSS software as a co-simulation mechanism. The study validated the simulation result on an 11.4 kV distribution feeder with a seven-buses transmission network consisting of underground cables and overhead lines, a secondary substation, and a wind turbine. The simulation results revealed that the proposed method is more effective than the traditional stochastic method. The authors proposed the technique as a planning tool for future DER integration. The authors in [26] have investigated the Bayesian Optimisation method. They proposed a computational framework for the probabilistic hosting capacity analysis (PHCA) that could easily fit with the uncertainties considered and efficiently measure the hosting capacity of the network. The study revealed that the proposed method could achieve about 25% higher accuracy and be about 75% less time-consuming compared to the traditional stochastic method. In [28], the authors investigated the multi-parametric programming method to reduce the complexity and calculation burden of the optimal power flow for estimating the hosting capacity without considering the probabilistic characteristics of the uncertainty of the network and distributed energy resources. The authors have proposed the multi-objective optimisation model in [30] and studied the method on wind power. The study found that the energy procurement from the upstream rises with the escalation of the hosting capacity, active power loss increases, and uncertainties decline. In [70], the authors investigated the stochastic analytic–probabilistic methodology for the hosting capacity analysis. The method embeds the probabilistic load flow to achieve computation efficiency. It focused on photovoltaic penetration. Impact factors, input, and analysis methods for the stochastic method have been summarised in Table 6.

Table 6. Stochastic Method.

Impact Factors	Input	Analysis Method	Reference
Voltage magnitude, current overloading	Active and reactive loads, active and reactive losses, line parameters, active and reactive power, DG power output	Power flow simulation	[6]
Over-voltage, Voltage unbalance, and Voltage deviation	Feeder characteristics, PV location, PV inverter power factor, volt/var control	Power flow optimisation using Monte Carlo procedure	[9]
Over-voltage, Voltage deviation, Voltage imbalance	Feeder parameters, load profile, solar irradiance, temperature, PV location, PV penetration level	Improved stochastic analysis method	[10]
Nodal real/reactive power, Voltage magnitude, Line flow limits	Nodal real and reactive injections, real and reactive flows on distribution lines, DER generation profile, DER installation scenario, real/reactive load profiles, DER location	Power flow optimisation	[26]
Location, frequency, and severity of feeder	Solar generation data, (re)active injections, inverter oversizing; DER penetration levels	MPP– OPF	[28]
Distribution feeders' voltages and currents, Cost of energy procurement from the upstream network, Power generation by RES	Load uncertainty, wind power generation, wind speed variation	Stochastic multi-objective optimisation model	[30]
Voltage limits, thermal capacity, voltage unbalance	Load profile, DER output profile	Analytic probabilistic load flow (PLF) using Monte-Carlo	[70]
Voltage magnitude	PV generation profile, load demand	Probabilistic power flow using Latin Hypercube Sampling with Cholesky Decomposition (LHS-DC)	[80]
Voltage magnitude and loading	DG capacity, grid parameters, DG configurations, location	Probabilistic power flow simulation	[81]
Over-voltage, under voltage, over current	PV location, size, type, and number, PV injection, consumer demand	Probabilistic power flow	[82]

- Relevant studies in stochastic methods:
The stochastic method has evolved to analyse the probabilistic nature of the input for the hosting capacity analysis of distribution networks. Voltage rise, current violation, protection issues, and stability have been studied in [6] to analyse the capacity of the distributed generation. The study used the power flow simulation to determine the hosting capacity of the three-phase distribution network consisting of radial low-voltage feeders. The authors in [9] applied the Monte Carlo simulation to study the hosting capacity of distribution networks with small-scale rooftop solar photovoltaic generating units. The study proposed feeder reconfiguration and volt-var optimisation to enhance the distribution network hosting capacity. In [10], over-voltage, voltage deviation, and voltage unbalance of distribution networks have been examined using an improved stochastic method. It also proposed the repetitive check mechanism to minimise errors due to the randomness of the PV unit deployment during the study. In [26], the authors examine the hosting capacity of the 56-node distribution network in California. The study found that the Bayesian optimisation provides about 25%

more hosting capacity results and about 70% less computation time than the nonlinear optimisation algorithm. Multi-parametric programming OPF has been investigated in [28] for hosting capacity analysis in IEEE 123-bus and 1160 bus feeders. In [30], the authors have estimated the hosting capacity of 69-bus radial and 152-bus distribution feeders using the stochastic multi-objective optimisation model. The study aimed to exploit the highest hosting capacity and lowest costs for integrating distributed energy resources such as wind power. In [80], the authors studied the over-voltage issues of a radial distribution network. They proposed the probabilistic power flow using Latin Hypercube Sampling with Cholesky Decomposition to analyse the hosting capacity with high penetration of rooftop PV generating units and associated inverters. The probabilistic power flow simulation has been conducted in [81] to determine the impact on the voltage magnitude and loading of a distribution network due to the high penetration of distributed energy resources. The authors in [82] studied the decoupled general polynomial chaos-based hosting capacity analysis tool for analysing the impact of planning and operational level uncertainties.

- Impact factors and required data:
  Hosting capacity analysis depends upon different input data and impact factors. In [6], the power flow simulation has been conducted for the feeder hosting capacity analysis based on the active and reactive loads, active and reactive losses, line parameters, active and reactive power, and DG power output. In [26], the authors considered the nodal real and reactive injections and real and reactive flows on distribution lines for calculating the hosting capacity of the distribution networks. They also considered the DER generation profile, DER installation scenario, real/reactive load profiles, and DER locations as the input data for the hosting capacity analysis considering nodal real/reactive power, voltage magnitude, and line flow limits. The authors in [30] assessed the load uncertainty, wind power generation output, and wind speed variation for the simulation using the stochastic multi-objective optimisation model for assessing the distribution feeder hosting capacity. In [70], the authors studied the load profile and DER output profile data to simulate the hosting capacity by the analytic probabilistic load flow (PLF) using Monte Carlo. PV generation profile and load demand data were studied in [80], for hosting the capacity analysis, taking the voltage magnitude as an impact factor. In [81], DG capacity, grid parameters, DG configurations, and locations have been considered input data for the hosting capacity study.

The stochastic method is a model-based hosting capacity analysis method that considers the probabilistic uncertainties of the distribution network and DER issues. It provides crucial information to the distribution network operators to plan for the future DER integration. The hosting capacity results depend on the number of uncertain problems considered. At the same time, it increases the complexity and time for calculation. This method generates millions of scenarios based on the network and DER uncertainties that require complex mathematical calculations and decrease reliability. It could not cover the real-time monitoring of the network and DER issues for sustainable integration and reliable operation. This method is unsuitable for real-time monitoring, data analysis, and future DER integration.

3.1.3. Streamlined Method

The streamlined method estimates the capability of the distribution network to integrate distributed energy resources through load flow and short circuit analysis, considering electrical characteristics and the consumer load profile [7]. This method could provide information on the location and capacity of the distributive energy resources for determining the future integration without the considerable improvement of the distribution network [7]. It conducts the simulation, considering feeders and distributed energy resources characteristics, such as line resistance, distribution transformers, system control devices, and levels and locations of consumer loads [71]. It executes a series of sensitivity analyses based on simplified algorithms instead of detailed network modelling. This method evaluates the time effect of DER, consumer load, and control mechanism on the hosting capacity of the distribution network through the simulation of time-series data acquired by the smart meter or other monitoring devices [71]. For calculating the hosting capacity analysis of the distribution network, this method considers voltage, thermal, protection, and power quality as regulating constraints [22]. The electrical characteristics of the network, uncertainties of the photovoltaic resources, and consumer load consumption behaviour are considered for the impact study through load flow and short circuit analysis [7]. This method is an effective tool for studying distributed energy resources forecast, network reconfiguration, intelligent inverter settings, and mitigation strategies of the distributed energy resources [71].

- Relevant Studies:
  In the streamlined method, the distribution feeder's realistic, optimistic, and conservative hosting capacity is calculated using the sensitivity test instead of the detailed power flow analysis [7]. Improvement in the simulation process, time, and required network resources for estimating the hosting capacity of a particular feeder has been proposed in different studies. In [7], the hosting capacity of each low-voltage distribution feeder has been analysed. Voltage limits, thermal capability, and control parameters have been considered for analysing the hosting capacity in [7,20,83]. In addition, the fault current has been considered a limiting factor for calculation. Time-series forecast data of photovoltaic power sources and load profiles have been taken as input values in [7]. In [83], the hosting capacity of distribution feeders has been analysed for the high penetration of DER. The node-by-node hosting capacity was simulated by deploying the utilised load profile and basic load flow model considering the thermal limit, voltage, and protection as limiting factors. The relevant studies on streamlined method have been summarised in Table 7.

Table 7. Streamlined Method.

Impact Factors	Input	Area	Reference
Voltage, Thermal, Control	Load profile, PV time-series output	PV	[7]
Voltage, Thermal, Control	Load profile, PV time-series output	DER	[83]

The streamlined method could generate realistic, optimistic, and conservative results of the hosting capacity [14]. The simulation complexity and result accuracy depend on the network and DER uncertainties. The estimated hosting capacity result may suffer from overestimation due to assumptions of this method, such as considering the DER output as fixed throughout the period. The grid operators could use this method to generate the future impacts of the photovoltaic sources on the distribution network. It requires a conducting detailed analysis to validate the result obtained using this method to make the final decision by the grid operators [8].

3.1.4. Iterative Method

In the iterative method of the hosting capacity analysis, the distributed energy resources are modelled on the existing distribution network to study the impact of the penetration on statutory limits of the power quality delivered to the customer. The power flow analysis is carried out by gradually increasing the penetration level, and violation is observed. The simulation studies the maximum allowable DER penetration at which the voltage, current, reverse power flow, protection criteria, thermal limits, and other power qualities violate the acceptable limit [10]. This method generates a series of DER deployment scenarios for accurate impact assessment at each node of the distribution networks to measure the hosting capacity [71,84].

Both non-linear and linear optimisation power flow analysis is conducted in the iterative method. In [85], the linearised iterative process has been applied to the IEEE 13-node test feeder circuit to investigate the effectiveness and measure performance. The study found that the linearised iterative method outperforms the non-linearised iterative method and reduces the computational time. The authors in [86] investigated the hosting capacity of the distribution network for integrating the photovoltaic energy resources concerning economic efficiency. They proposed the bi-level optimisation dispatch method based on iterative particle swarm optimisation method. They demonstrated the proposed method on the modified PG&E 69-bus and IEEE 123-bus radial distribution systems. They concluded that the proposed linear analysis system has about ten times higher computation speed than the non-linear iterative power flow analysis.

The iterative method requires much data, time, and computational effort. The complexity increases with the increased network nodes and distributive energy resources [71]. It provides a comparatively accurate hosting capacity value [8]. This method is preferable for calculating the distribution network node DER's hosting capacity.

3.1.5. Hybrid Method

The hybrid method is the modified version of stochastic and iterative methods. The trained periodic increment is used to overcome the computational burden in the hybrid method. The iterative process needs to be conducted more meticulously for the hosting capacity analysis of the network. Instead, a carefully chosen incremental iterative process helps to find out the hosting capacity of the distributed resources within the tolerable limits without violating the statutory limitations of the power [71]. In this method, simulation data are readily available, agile to implement, consume less processing time, and generate relatively accurate results [8].

3.1.6. Capacity Constraint-Based Method (CCBM)

The Capacity Constraint-Based Method considers the forecasted value of power supply, load demand pattern, distribution network stability, over-voltage limit, under voltage limit, current limit, and operation constraints for calculating the hosting capacity. The optimisation framework studies the capacity constraints of the distribution network and applies it incrementally throughout the network to conduct a power flow analysis [71]. This method does not consider the uncertainties of the network and distributed energy resources. It depends on the historical data collected from the smart meters connected to the customer end. The maximum voltage occurrence and aggregated power demand data set are extracted from the smart meter data.

This method is highly dependent on historical data collected from smart meters. The accuracy of the estimated hosting capacity depends on the smart meter data quality and data reliability. Moreover, this method does not consider variables of the distribution network and distributed energy resources; the simulated value of the hosting capacity could not represent the real scenario. This value could only be utilised for reference purposes.

3.2. Comparative Analysis of Conventional Hosting Capacity Methods

Different hosting capacity analysis methods are distinct from each other. The iterative method is complex but gives comparatively accurate hosting capacity results [14]. The Capacity Constraint-Based Model does not depend on any network model [25]. On the other hand, the dependency on smart meter data has limited its application [71]. Table 8 provides a comparison among the different hosting capacity analysis characteristics:

Table 8. Comparison among Conventional Hosting Capacity Analysis Methods.

Features	**Conventional Hosting Capacity Analysis Methods**					
	Deterministic	**Stochastic**	**Streamlined**	**Iterative**	**Hybrid**	**CCBM**
Input Data	Easy	Complex	Moderate	Complex	Easy	Moderate
Execution	Easy	Complex	Easy	Complex	Agile	Moderate
Uncertainties	No	Yes	Yes	Yes	No	No
Simulation	Worst-Case Based	Realistic Scenario Based	Realistic Scenario Based	Realistic Scenario Based	Realistic Scenario Based	Trained Model Based
Temporal Relationship	Missing	Missing	Included	Included	Included	Missing
Processing Speed	Rapid	Moderate	Slow	Slow	Moderate	Moderate
Time	Speedy	Slow	Speedy	Slow	Speedy	Moderate
Computation Effort	Less	High	High	Higher	Less	Moderate
Scalability	Easy	Complex	Easy	Complex	Moderate	Complex
Output Interpretation	Easy	Complex	Easy	Easy	Easy	Complex
Model-Based	Yes	Yes	Yes	Yes	Yes	No

Among the conventional hosting capacity analysis methods, the deterministic method depends on the worst-case-based scenario of the distribution network. It requires less computation effort as it does not consider the DER and network uncertainty. The hosting capacity result obtained using this method could only be used as a reference. The stochastic, streamlined, iterative and hybrid methods perform the realistic-scenario-based simulation to estimate the feeder hosting capacity. The stochastic method is a relatively complex process, takes more computation effort and consumes more time. The streamlined method considers the DER and network uncertainties to analyse the hosting capacity of the network. It performs the simulation based on a simplified algorithm instead of the detailed network model. Therefore, it provides a higher processing speed and takes less computation time. Though the iterative hosting capacity analysis method is comparatively complex, it gives more accurate results through a realistic-scenario-based simulation. The hybrid method combines algorithms used in the deterministic, stochastic, streamlined, and iterative methods. This method incorporates the benefits and eliminates the drawback of all other methods. The CCBM method does not rely on the network model. Instead, it is highly dependent on the historical data of the DER generation, load and other network components. It does not provide the realistic hosting capacity of the network feeder. Therefore, the hosting capacity results could only be used as a reference.

Time series analysis, Iterative, and capacity constraint-based methods highly depend on available data. The deterministic method is simple, tests fewer scenarios, and takes less simulation time [14]. Time series analysis, iterative and hybrid methods generate more accurate hosting capacity results, as realistic network data are simulated in these methods [68]. The hosting capacity methods based on the data requirement, simulation time, scenario tested, and output accuracy can be summarised in Table 9.

Table 9. Comparison among different Hosting Capacity Methods.

Methods	Characteristics				
	Data Requirement	**Difficulty Level**	**Simulation Period**	**Scenario Requirement**	**Output Accuracy**
Deterministic	Simple	Simple	Low	Worst Case Based	Approximate
Stochastic	Medium	Complex	High	Realistic Scenario	Accurate
Streamlined	Medium	Complex	Medium	Realistic Scenario	Approximate
Time Series	High	Complex	High	Realistic Scenario	Accurate
Optimisation Based	Medium	Complex	Medium	Realistic Scenario	Exact
Iterative	High	Complex	High	Realistic Scenario	Accurate
Hybrid	Medium	Medium	Medium	Realistic Scenario	Accurate
CCBM	High	Low	Low	Not Required	Approximate

The deterministic hosting capacity analysis method is less dependent on network and DER data. In contrast, time series analysis, iterative, and CCBM hosting capacity analysis methods highly rely on DER and network data. The deterministic approach does not incorporate DER and network uncertainty. It provides an approximate value of the hosting capacity value of the network with DER that could be used as a reference. The stochastic, time series, and iterative hosting capacity analysis methods provide relatively more accurate results. The stochastic approach is model-based, difficult to simulate and consumes more computation time, but it gives more accurate hosting capacity results. The time series analysis could incorporate the time effect of DER and network uncertainties for hosting the capacity analysis, generating more precise results for the network planners and DSO.

3.3. Artificial Intelligence Approach of Hosting Capacity Analysis

The electricity power network is a complex network of generation, transmission, distribution, and control equipment. The modern power network consists of sophisticated communication systems, power conversion equipment, renewable energy resources, power storage networks, and information processing systems. The growing trend of digitisation, decentralisation, and real-time monitoring of power networks requires a high volume of data collection, analysis, and decision-making capabilities for sustainable operation, quick decision, and economic viability. Artificial Intelligence has great potential for managing energy supply, reliable operation, demand forecasting, and distributed energy resources' integration through intelligent decision-making tools [87]. The growing demand for green energy has triggered the integration of a large number of distributed energy resources and energy storage devices with the power network that requires real-time network data analysis integration sustainability, network stability, operation reliability, and economic value [88]. The operational uncertainties of DER, EV, energy storage devices, power conversation system, and uncertain load consumption pattern involves the analysis of a large number of data [89]. Traditional analysis tools are unable to fulfil the requirement of the modern electricity network [90]. Artificial Intelligence algorithms could be very useful for the analysis of dynamic behaviour, forecasting, integration, disturbance events, and cyber security of the electricity network with a high penetration of DER and energy storage devices [88].

The network operators have to face significant complexity in the power network design, operation, and integration for an increasing number of distributed energy resources [35]. Artificial Intelligence could overcome the ever-increasing technical and operational complexity of integrating distributed renewable energy resources with the distribution network [91]. It could be used for power output prediction from renewable resources, photovoltaic power optimisation, solar irradiance, and wind speed prediction, risk and tariff optimisation, system stability, and integration. Artificial intelligence algorithms could be static or dynamic based on the input data and objective functions. Depending on the system and problems to be analysed, different artificial intelligence methods have been proposed such as the Meta-heuristic methods genetic algorithm (GA), particle swarm optimisation (PSO), simulated annealing (SA), random forest (RF), k-Nearest Neighbours (kNN), support vector machine (SVM), and artificial neural network (ANN) [92]. Power output forecasting has gained much attention for the sustainable integration of renewable energy resources with the power network. The artificial intelligence algorithms could increase the efficiency, effectiveness, and potentiality of the real-time DER monitoring and achieve a maximum potential power from these resources [89]. The stack auto-encoder (SAE), deep belief network (DBN), deep recurrent neural network (DRNN), stacked extreme learning machine (SELM), deep reinforcement learning (DEL), and deep convolution neural network (DCNN) are a widely used deep learning algorithm for forecasting renewable energy [86,87,89].

In [35], the authors studied the deep-learning-based Spatial-Temporal Long Short-term memory (ST-LSTM) algorithm for calculating the real-time hosting capacity of each feeder of the distribution network by correlating the spatial and temporal network and DER data. In the proposed algorithm, they have introduced a cloud-based end-to-end solar energy optimisation platform (e-SEOP) for accumulating and analysing data gathered from a dynamically calculated hosting capacity and real-time DER control system. The study introduced a sensitivity gate for increasing the output accuracy. The power consumption forecasting is essential for the integration of DER with the network. In [38], the authors investigated the deep learning algorithm-based k-means clustering-based convolutional neural networks and a long short-term memory (k-CNNLSTM) model for the reliable forecasting of energy consumption. Using a case study and comparing results using various tools and techniques, the authors have concluded that the proposed k-CNNLSTM model provides more accurate demand forecasting of energy consumption. The improved load forecasting results may help the network operator to manage the power demand more efficiently and effectively [38]. In [39], the low-voltage grid has been classified based on the network, simulation, and graph information. They proposed the support vector machine (SVM) for analysing low-voltage grid characteristic parameters. The researchers in [45] studied the supervised deep learning algorithm for forecasting the energy demand at the district level so that the designers, planners, and administrators could utilise the forecasted result. They examined the One-Step Secant Back propagation Neural Networks (OSSB-NN) and the BFGS Quasi-Newton Back propagation (BFGS-QNB) using-real time consumption and climate data. In [93], the authors proposed swarm intelligence optimisation and data processing for estimating the potentiality of wind energy and forecasting the wind speed that would help reduce the operating cost of the wind power generating stations. In [94], the researchers introduced the deep-learning-based framework (D-FED) for calculating the future energy demand, forecasting the electricity demand in real-time, and estimating the dependencies of the load demand. They used the Short Long-Term Memory Network moving window for their proposed framework. The artificial intelligence methods for the distributed energy resources could be categorised as data-driven methods and optimisation-based methods.

3.3.1. Data-Driven Methods

The hosting capacity is not a static value of the integration capability of the power network. Rather, it is the estimation of the coordinated effects of different impact factors that express the capability of the power network to accommodate the maximum power from the distributed energy resources without violating the power quality limits. The model-based methods depend on the network's worst-case scenarios, considering different DER penetration levels, network characteristics, and consumer load demands [95]. The different scenarios representing the minimum or maximum allowable limits of the power indicators such as voltage level, current injection, thermal overloading, load demand, and DER penetration could not represent realistic scenarios of the network. Such approaches tend to overestimate or underestimate the hosting capacity of the network. Moreover, changing any parameter requires different scenarios that may generate millions of scenarios' simulation burdens.

Model-based approaches become more complex to handle the time-based data for the hosting capacity analysis. Therefore, they tend to be inefficient, time-consuming, and error-prone hosting capacity analysis processes. The data-driven hosting capacity analysis methods collect time-series input data of the network components, consumer load variation, and DER penetration for estimating the hosting capacity of the distribution network. It considers uncertainties of the DER integration based on real-time data. Different artificial intelligence algorithms could be utilised to encompass the probabilistic nature of the network, load, and DER parameters. It could train the learning model using offline or online data to calculate the real-time hosting capacity [35]. The data-driven methods could enhance the computational capability and output accuracy of the hosting capacity of the distribution network.

- Machine learning:
  The high penetration of distributed energy resources in the high and medium voltage distribution network may affect the voltage profile and power quality. The active power control and reactive power generation capability of the network could positively impact the stability and reliability of the network [37]. Machine-learning-based approaches have been studied for mitigating the adverse impacts of the high penetration of renewable energy resources. In [37], the Static Multi-agent Reinforcement Learning (MARL) algorithm was studied to enhance the distribution network's hosting capacity. The voltage flexibility of the network was analysed using the primary voltage, line, and transformer loading as input parameters. The method was tested using the Monte-Carlo-based power flow simulation on the modified IEEE 34 bus system with the Converter-interfaced Generation (CIG). The authors achieved about 7.53% of voltage flexibility using their proposed machine-learning-based method. The feasible and infeasible nature of the Optimal Power Flow (OPF) analysis was incorporated in [28] to achieve rapid and scalable solutions for probabilistic hosting capacity analysis. The proposed method solved a fraction of OPF to achieve speedy results compared to the traditional methods. The Support Vector Machine (SVM) approach was studied in [39]. In this study, the authors have classified the low voltage distribution grid for hosting a capacity analysis based on the grid features, simulation features, and graph features. The study found that the reinforcement of the grid, utilisation of innovative technologies, and control of the reactive power could enhance the hosting capacity of the distribution network for integrating distributed energy resources. In [96], the network reconfiguration and Distributed Generators' distribution were studied using the Location-improved Sine-Cosine Algorithm (LSCA). The voltage stability and active power loss were analysed to estimate the hosting capacity of the distribution network by applying the integrated forward-backward-based load flow analysis.
- Deep learning:
  The deep learning algorithms could enhance the performance of the hosting capacity analysis through training neural networks. In [35], the Spatial-Temporal LSTM (ST-LSTM) learning model was studied for predicting the real-time hosting capacity of each feeder of the distribution network. The deep learning algorithm kCNN-LSTM was studied in [38] for forecasting the energy consumption. The model was tested at the four-storied building in the Indian Institute of Technology (IIT), Bombay, India. In [93], the authors studied the Multiple Swarm Intelligence Optimisation (MSIO) algorithm for forecasting and estimating the potential of the power generated from

wind energy sources. In [94], the authors considered the long-term historical data for electricity demand forecasting using the long short-term memory (LSTM) algorithm.

3.3.2. AI in Hosting Capacity Analysis

The real-time hosting capacity analysis requires a time-series data analysis for the reliable operation and sustainable integration of the DER with the distribution network. Different artificial intelligence techniques were proposed to estimate the hosting capacity using the non-linear behaviour of different uncertain parameters [47]. Researchers proposed different artificial intelligence techniques for the hosting capacity analysis (Table 10).

Table 10. Hosting Capacity Analysis Using AI Techniques.

Area of Study	Algorithm Used	Objective Function	Reference
Photovoltaic hosting capacity analysis	Multi-parametric programming (MPP) OPF	Fast and scalable solutions for PHCA studies	[28]
Distribution grid hosting capacity in real-time	Deep-learning-based LSTM	Real-time prediction of Hosting Capacity for each feeder	[35]
Converter-interfaced generators (CIGs) integration	Static multi-agent reinforcement learning (MARL) algorithm	Maximising hosting capacity and voltage flexibility	[37]
Energy consumption forecasting	Deep-learning-based kCNN-LSTM	Energy consumption forecast	[38]
Low voltage grid	Support vector machines (SVM)	Low-voltage grid classification for hosting capacity	[39]
Energy demand predictions	Improved sine cosine optimisation algorithm-based LSTM (ISCOA-LSTM)	energy consumption forecasting	[44]
Energy requirement forecasting	OSSB-NN and BFGS-QNB	Load demand forecasting	[45]
Home PV system	Policy function approximation (PFA)	Impact of PV-battery systems on distribution networks	[46]
Optimal locations for new DERs	TLBO and HBMO algorithms	Cost, losses, and voltage deviation	[47]
PV System	Multiple swarm intelligence optimisation algorithm	Wind energy potential analysis, wind speed forecasting	[93]
Electricity consumption forecasting	Long short-term memory network	Timestamp prediction of future electricity demand	[94]

3.3.3. Optimisation

Integrating distributed energy resources with the power network would be economically profitable and technically sustainable by optimising distribution network parameters, the network and DER control model, the DER output, and the demand uncertainty model, as well as the DER output forecasting model. The sustainable integration of distributed renewable energy resources and energy storage devices within the electricity network requires the analysis of the microscopic information for network stability, reliability, and economic operation [88]. The varying nature of the power generated from the distributed energy resources, energy storage devices, power conversation electronic equipment, and uncertain load consumption pattern involves analysing a considerable amount of real-time data [89]. Traditional analysis tools are unable to fulfil the requirement of the modern electricity network [90]. Artificial Intelligence algorithms could be very useful for the analysis of dynamic behaviour, forecasting, integration, disturbance events, and cyber security of the electricity network with a high penetration of DER and energy storage devices [88].

In [38], the authors investigated the deep learning algorithm-based K-means clustering-based convolutional neural networks and long short-term memory (k-CNNLSTM) model for the reliable forecasting of energy consumption. Using a case study and comparing the results using various tools and techniques, the authors have concluded that the proposed k-CNNLSTM model provides more accurate demand forecasting of energy consumption.

The improved load forecasting results may help the network operator to manage the power demand more efficiently and effectively [38]. In [39], the low-voltage grid was classified based on the grid information such as the network feature, simulation feature, and graph feature. They proposed the support vector machine (SVM) for analysing low-voltage grid characteristic parameters. The researchers in [45] studied the supervised deep learning algorithm for forecasting the energy demand at the district level so that the designers, planners, and administrators could utilise the predicted result. They examined the One-step secant back propagation neural networks (OSSB-NN) and BFGS Quasi-Newton back propagation (BFGS-QNB) using the real time consumption and climate data. In [89], the authors reviewed the efficiency, effectiveness, and potentiality of the artificial intelligence algorithms using deep learning techniques for forecasting the renewable energy output. The sparse autoencoder (SAE), deep belief network (DBN), deep recurrent neural network (DRNN), stacked extreme learning machine (SELM), deep reinforcement learning (DEL), and deep convolutional neural network (DCNN) are a widely used deep learning algorithm for forecasting the renewable energy. Power consumption forecasting is essential for the integration of DER with the network. In [93], the authors proposed a swarm intelligence optimisation and data processing for estimating the potentiality of wind energy and forecasting the wind speed that would help reduce the operating cost of the wind power generating stations. In [94], the authors introduced the deep-learning-based framework (D-FED) for calculating the future energy demand, forecasting the electricity demand in real-time and estimating the dependencies of the load demand. They used the short long-term memory network moving window for the proposed framework.

3.4. Efficiency of Different Hosting Capacity Analysis Approaches

Different hosting capacity approaches have adopted different analysis models. The hosting capacity output varies based on the objective functions and constraints considered for analysis. Researchers consider the standard distribution network such as IEEE test networks, European low voltage networks, and other standard networks. The methods or models are also verified on practical distribution network models based on real data to simulate the practical scenarios. The study in [22,28,33,97] used IEEE distribution networks for validating their proposed models. The practical distribution network was used for validating the model in [11,18,26,29,36,68,98]. The European low voltage network was adopted in [40].

The hosting capacity in different studies varies due to the various assumptions, constraints and networks considered. In [29], the study found up to 70% of the EV share on the distribution network, whereas in [97], 86% of hosting capacity was observed at the suburban feeder network in the IEEE 33-bus system. In [98], the hosting capacity analysis accuracy was highlighted. The study found about 90% output accuracy for the PV hosting capacity analysis using the Monte Carlo-based hourly stochastic analysis framework. The use cases, models, objectives and obtained hosting capacity results are summarised in Table 11.

Table 11. Hosting capacity analysis method results.

Application Scenario	Method	Objective	Results	Reference
Distribution network with 15 feeders	Monte Carlo Procedure; Stochastic Analysis Approach	To investigate the impact of PV location, voltage regulator, and power factor on hosting capacity	Up to 71.8% hosting capacity of feeder achieved with restricted PV location	[9]
A 11.4 kV distribution feeder with seven buses	Improved stochastic analysis method	Analysis of PV hosting capacity	Up to 400% PV penetration observed using PV inverter Volt/VAR control	[10]
Real distribution network consisting of 943 nodes	Dynamic distributed photovoltaic hosting capacity methodology	Dynamic hosting capacity estimation with distributed PV sources	Dynamic hosting capacity achieved up to 60–20% higher compared to static hosting capacity	[11]
Swedish distribution network with 51 secondary substation and 34 customers	NIS analysis software	To investigate the PV penetration level	A 40% PV penetration observed	[18]
The 33-bus distribution system	Mixed-integer linear programming model	Enhancing hosting capacity with DG and EV penetration with the network	A 66.67% DG penetration achieved with EV injection with the network	[22]
A 56-node South California Edison distribution network	Probabilistic Hosting Capacity Analysis via Bayesian Optimisation	Optimal DER Location	A 25% higher hosting capacity with 70% computation time saving	[26]
IEEE 123-bus feeder	Multi-parametric Programming (MPP)-aided Probabilistic Hosting Capacity Analysis (PHCA) method	Acceleration of hosting capacity analysis	A 10 to 20 times faster hosting capacity analysis acceleration	[28]
LV radial network proposed by Task Force C6.04.02 CIGRÉ	DG hosting capacity approximation using the k-NN regression technique	Hosting capacity analysis using Time-of-Tariff (TOU) for EVs	Up to 70% of the EVs share achieved	[29]
Standard radial 69 bus distribution feeder and a practical 152 bus distribution system	Stochastic multi-objectives optimisation model using Mixed Integer Nonlinear Programming (MINLP) optimisation method	Losses and their associated cost	Reduced active power loss	[30]
IEEE-33 radial distribution system	Continuation Power Flow (CPF)-based voltage stability analysis method	Optimal Hosting capacity and Computation time	Reduced observed bus number, scenarios to be analysed and computation time compared to stochastic method	[33]
European LV feeders	General polynomial chaos-based probabilistic power flow	Planning and operation uncertainties of the hosting capacity analysis	Hosting capacity increased three times by allowing a 25% higher grid limit	[40]
Medium voltage radial feeder with 19 feeder circuits and 7084 consumer connections	Hybrid method	Impact of load and PV generation uncertainty on hosting capacity analysis	Observed up to 85.70% penetration level	[68]

Table 11. *Cont.*

Application Scenario	Method	Objective	Results	Reference
Low voltage distribution network of New Zealand EDBs with almost 30,000 customer connection points	DG hosting capacity approximation using k-NN regression technique	DG hosting capacity analysis	The median distribution error achieved below 10% for all DG penetration level	[36]
IEEE 33-bus system	Monte-Carlo simulation-based PV hosting capacity analysis with respect to economic constraint	Technical and economic limiting factors on hosting capacity	A 40% reduced network costs; 85%, 86%, and 76% hosting capacity in rural, suburban, and urban areas, respectively	[97]
A 12.47-KV distribution network with 24 MVA substation transformer, 1196 MW of PV generation and 1218 customer connections	Monte-Carlo-based hourly stochastic analysis framework	PV hosting capacity analysis	More than 90% accuracy is obtained	[98]

4. Future Research Directions

The application of artificial intelligence techniques is a relatively less explored area in the hosting capacity analysis of the low voltage distribution network. Various artificial intelligence techniques could be excellent tools for examining power quality parameters. The hosting capacity analysis is concerned with measuring the capability of the distribution network to withstand the additional DER within the allowable power quality limits. Artificial intelligence techniques can estimate the parameters on a real-time basis, enhance computational efficiency and increase output accuracy. Instead of conventional methods, artificial intelligence techniques could be utilised for measuring the real power injection to the distribution network from distributed energy resources, real and reactive power curtailment, and assessing the required network augmentation. The real-time forecasting of the power generation from the DER and consumer demand could play a crucial role for the hosting capacity analysis and low voltage distribution network management for the distribution network operators. Artificial intelligence could be a powerful tool for the real-time power generation and consumption forecasting that would boost the performance of the network. Researchers should pay attention to the real-time measurement of all network parameters and respond accordingly to ensure consumers' sustainable and reliable power supply.

5. Conclusions

In this paper, relevant works were studied to explore the state-of-the-art hosting capacity analysis methods and DER integration challenges faced by the distribution system operators. It also highlights the research gap in different literature investigating the methods and algorithms used for analysing various aspects of power flow and hosting capacity. It examined various impact factors that affect the hosting capacity of the distribution network with a high penetration of DER. It also discussed different hosting capacity analysis methods investigated by different researchers. This paper concludes that the artificial intelligence-based hosting capacity analysis methods could be better alternative for a real-time hosting capacity analysis and sustainable integration of the DER with medium and low voltage distribution network.

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