Dynamic Hosting Capacity within DERMS

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***Abstract*— Uncertainties associated to Distributed Energy Resources (DER) generation and demand are introduced into Hosting Capacity evaluation by performing a Monte Carlo based OPF analysis with curtailment minimisation as objective function. This approach obtains curtailment distributions, from which risk analysis is performed to provide information for investors with the aim of incentivising investment in DERs. These are beneficial for the grid as they provide flexibility and reliability.**

Keywords—Hosting Capacity, DER, curtailment

I. Introduction

Hosting Capacity (HC) is defined as the ability of a system to host generation without the grid reaching a critical operating point. HC is typically used in the field of renewable generation integration. If generation exceeds the HC it implies that at least one electrical variable of the grid (voltage, flow through a line, etc.) exceeds a limit for a certain time.

In recent years, developed countries have set various environmental goals. For example, the state of California is aiming for 60% of energy to be produced by renewables by 2030 [1], and Europe has set the goal of increasing energy efficiency while increasing the integration of renewable energy sources [2]. These initiatives have caused investment in DER to grow considerably in recent years. According to [3], Distributed Photovoltaic (DPV) will grow at a rate of 6.1% per year from 2020 to 2050, causing a paradigm shift in the electricity system. The increased penetration of DER can cause problems in the distribution grid such as overvoltages at nodes, overcurrents on lines, reverse flows and problems with power quality due to connected electronic equipment [4].

Traditionally, the power grid worked as follows: power was generated at generation plants and transported to customers (most of whom were located on the distribution network) via the transport and distribution networks. Distribution system operators (DSOs), when planning investments in the network, had only to take a pattern of demand growth and plan equipment reinforcements. However, the upward trend in DER installation coupled with changes in consumption patterns, complicates the planning of the distribution network using the traditional methodology.

To avoid blind investments in grid reinforcement, DSOs adopted the HC term, which was first introduced in 2004 by Bollen et al, [5]. The first and actual approach to determine HC value is static. Points of maximum generation and minimum consumption are taken, then the cases are simulated using a power flow (PF) until a certain installed capacity exceeds network operational limits. This value becomes the HC of the distribution network. This method has been valid until the interest in DER investment exploded. Without question, this value is typically very conservative and highly unlikely as it combines an instant of minimum demand (typically at night) with an instant of maximum generation (in case of midday PV generation).

The approach to increase the HC of the distribution grid is named Dynamic Hosting Capacity (DHC). This new methodology is stochastic and can consider uncertainties of production, consumption and DER locations when determining the HC of the grid. In addition, with inverter control schemes, an increase in HC can be obtained by reducing for short periods of time the power injected by DERs into the grid, this is also known as curtailment. This new methodology increases the HC.

The project objective is to implement a DHC algorithm that reframes the HC problem and determines the new HC of distribution systems using a DHC approach.

II. State of the Art

This section will describe the developments to date in the Hosting Capacity environment. First, the criteria that are commonly used to determine HC will be described, then the most common techniques that can be used to increase HC will be discussed. Thirdly, the existing methodologies that are being used to determine HC will be explained. Then, the active control techniques will be described. Finally, the last section of this chapter shows a briefing of a market report, which analyses the existing DERMS products, the players in the market and those who are addressing Hosting Capacity.

A. Hosting Capacity crieria.

The results obtained from the HC will depend on the criteria previously established. These criteria are the technical limits of the distribution network. The implementation of DER in the distribution network can cause the technical limits of the distribution network to be reached; these limits are used in the algorithms to determine the HC level that the distribution network can accommodate without it reaching critical operating points. The most studied limits according to [6], [7] are: thermal limits, voltage limits, limits associated with the protections and, finally, limits associated to the quality of service.

Out of all the criteria, the frequency of occurance is not the same; in most of the studies carried out, over voltages and over currents are the two most frequently reached limits [5], [6], [8].

B. Hosting Capacity Enhancement Techniques

The techniques to increase the Hosting Capacity try to avoid reaching the limits of the system. In [6], methods that try to avoid reaching the upper limit of voltages in the nodes are studied, on the other hand, in [5], besides from commenting on the methods to regulate the voltages, it also introduces methods to mitigate harmonics and comments on reinforcements as a method to increase the HC. The last two techniques will not be discussed, the first one because harmonics do not usually cause problems and the second one because this work aims to find ways to increase the HC without resorting to wire solutions, and therefore, grid reinforcements will not be considered further.

C. *Existing Methodologies for determining Hosting Capacity*

The system capacity can be broken down into three regions [6]. The three regions are depicted in Fig 1, and are denoted as A, B and C. Fig 1 assesses the probability of an electricity variable reaching its limits as a function of the level of installed capacity. In region A, the probability of exceeding any operational limit is zero for all installed capacity levels. Region B comprises those installed capacity values where there is a risk associated with exceeding network limits, the higher the installed capacity, the higher the risk. Finally, region C is where the system limits for the level of installed capacity will always be exceeded. Continuing, there are two points of interest. These are indicated in Fig 1 as HC minimum (Minimum Hosting Capacity) and HC maximum (Maximum Hosting Capacity), the first is the boundary between region A and B, while the second is the boundary between region B and C.

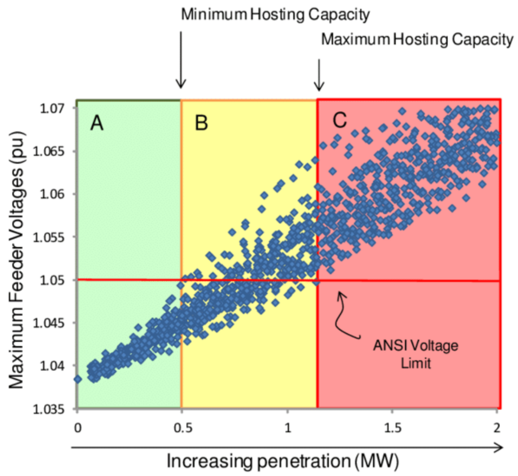

Fig 1: Hosting Capacity Regions

The traditional method to determine the HC tries to find the value of the minimum HC, as this way of assessing the HC is becoming obsolete, now the region B has taken more interest. The existing mathematical methods for estimating the HC in region B are classified as follows [6], [9]:

1. Optimization problem: Optimization problems tend to converge towards the maximum HC, as the objective function is usually focused on maximising the installed capacity. Three types of optimisation problems are distinguished in [6]:
    a. Robust optimization: Probabilistic distributions of generation and consumption are not needed, only their limits. Decisions are made assuming a worst-case scenario within the previously defined uncertainty interval.
    b. Stochastic Optimization: Uncertainties are modelled as random variables with their probability functions. Scenarios of these variables need to be generated, which are then solved simultaneously.
    c. Distributionally Robust Optimization (DRO): It assumes that probability functions are impossible to achieve, but it does consider generation and consumption predictions as values within a confidence interval.
2. Analytical Method: Analytical methods are deterministic problems and do not consider the uncertainties associated with generation, consumption and location of DER installations.
3. Monte-Carlo: Generates multiple scenarios to model uncertainties and performs a load flow to each scenario to determine the HC.

When estimating the HC of a network, [10] defines 3 variables with uncertainty which are: the location of DER installations, the variation in demand, uncertainty in generation. For computational simplicity, DHC methods do not consider the uncertainty associated with at least one of the variables.

The methodology can be summarised by dividing the mathematical methods into two groups, deterministic and probabilistic. The first group uses those mathematical models to determine the HC that do not consider the uncertainties of the variables, the second group will consider the uncertainties and their results will be probabilistic distributions.

D. *Active Control of the Distribution Network*

In a distribution network with high DER penetration, voltages at the nodes are often one of the biggest problems that the DSOs encounter [11], [12]. One of the ways to increase the HC of the network without the need to invest in reinforcements is the asset management in the distribution network. This involves modifying the operating point of the equipment connected to the network so that the network does not go outside its operating limits. The most commonly used techniques to control the grid and simultaneously increase HC are the modification of the taps of an On-Load Tap Changers (OLTC) transformer at the substation of the feeder, and the control of active and reactive power using the inverters of DER installations.

1) *OLTC Transformer Control*

Distribution networks are operated radially and the OLTC is located at the MV/LV substation from the feeder. The OLTC allows the transformer tap to be changed while the transformer is under load, this feature enables the system operator to control the voltages at the feeder in real time. The control techniques (according to [12], [13]) of an OLTC are as follows:

1. Transformer secondary voltage control: This method modifies the OLTC taps to keep the secondary voltage as close as possible to a predefined point.
2. Control of the voltages at the furthest points from the transformer: To carry out this control it is necessary to have measuring equipment installed at the furthest point from the feeder and a telecommunications system to transmit the status of the node to the transformer, the OLTC will change the tap to maintain the voltages at the end of the feeder within acceptable limits. This method would be effective if there were no DER connected, since as the networks are radial, the voltage at the furthest point from the substation will always be the smallest. However, with DER installations this does

not need be the case and tap changing can lead to overvoltages at other points in the network.

3. Voltage control at all nodes: OLTC shall modify its taps so that all network node voltages are at acceptable operating points.
4. Temporal control: This method consists of changing the tap in function of time, allowing less conservative values (closer to the lower and upper boundaries) to be adopted in low demand scenarios and more conservative scenarios in high demand scenarios.

2) Reactive Power Control

Reactive power control is based on using the inverter to inject or consume reactive power so that the grid voltages are within acceptable ranges. There are two popular reactive power controls [11], [12]. The first one is based on controlling the reactive power consumed using the Constant Power Factor Mode (CPFM), which is a function of the net active power injected. The second control determines the reactive power that the equipment will consume or inject as a function of the voltage at the node, this is known as Volt-Var Operation Mode (VVOM).

The operation of the VVOM control is shown in Fig 2, which represents the power being injected or consumed on the vertical axis and the voltages on the horizontal axis. As can be seen, when the voltage is below 0.92 p.u., the inverter injects the maximum reactive power. If the voltage is within an acceptable range (0.94-1.06 p.u.) the inverter will not consume or inject reactive power, once the voltage exceeds 1.06 p.u. it will start to consume reactive power, the consumption will increase linearly from zero to the maximum reactive power as a function of the voltage at the node.

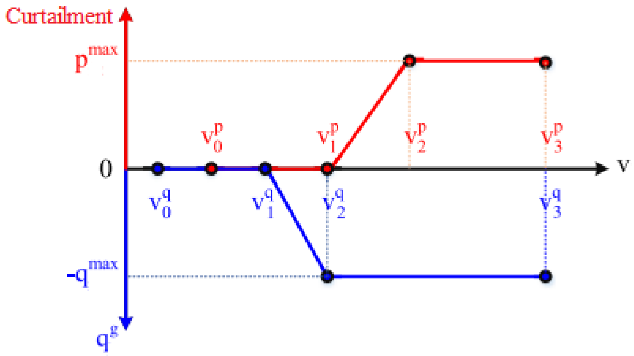

Fig 2: Active and Reactive Power Control in function of node Voltages.

3) Active Power Control

Inverters also allow to control the active power that can be fed into the grid, active power control in distribution networks tends to be more efficient than reactive power control due to the X/R ratio. Despite being more efficient, the disadvantage is that it reduces the income of the owners of the DER installations proportionally to the power curtailed. This method makes it possible to increase HC. However, the system operator and DER owners must come to an agreement to see how much active power can be curtailed, as too much active power curtailment can cause investors to reconsider investing in DER facilities. The most common control architectures are as follows:

1. Fixed maximum power: This control strategy is presented in [14], on it, the equipment can only inject up to 70% of its nominal power, when the installation is generating more than this, the active power will be curtailed.
2. Volt-Watt Operation Mode (VWOM): This operating mode controls the active power injected as a function of the voltage at the node. The operation of this control scheme is shown in Fig 2, the active power is identified by the blue curve. If the reactive control is ignored, the voltage-dependent active power control is based on starting to curtail active power injections once the voltage exceeds a certain value.
3. Volt-Var-Watt Operation Mode (VVWOM): Combines the VWOM and VVOM control schemes, the operation is shown in Fig 2, the objective of combining these two schemes is to reduce curtailment. To do this, first the reactive power is controlled until it reaches its maximum, when it is no longer possible to consume more reactive power and the voltage exceeds a certain value, the active power injected will start to be reduced until the voltage returns to within the operating threshold.

III. MODEL DESCRIPTION

To introduce the uncertainties associated with generation and demand into the model, a Monte Carlo based OPF approach has been implemented. For it, in each of the scenarios created, an OPF will be run with curtailment minimisation as objective function.

Since the historical data contains hourly and monthly information, it is desired to take advantage of this to transfer this information into the output data. To achieve this, as shown in Fig 3, three variables are generated, m, h and MC, where:

- m = stands for the month group that will be evaluated, in our case the analysis will be carried out monthly.
- h = stands for the hour group to be evaluated, for example, in [10] a clustering analysis is made to group the hours into homogeneous groups, on this model, the analysis will be carried out in an hourly basis.
- MC = stands for the number of samples that we want to obtain for each hour, this value is up to the user, the higher the value, the higher the computational burden and the longer it will take to run the algorithm.

The goal of the algorithm is to get MC samples for every hour and for every month of the year, the number of total runs will be obtained following equation (1). In this case, m will be equal to 12, h will equal 24 and MC will take the value of 60, resulting in 17,280 runs.

$$m \times h \times MC = n^{\circ}\ of\ runs \qquad (1)$$

For every run the algorithm does the following process: firstly, the technology to be installed, the capacity and the location of the plant will be specified. Second, random samples from the input variables are selected, these are load and generation values. These values come from historical data. The objective function of the OPF is active power curtailment minimisation. Moreover, the OPF has a VWOM control which manages the voltages at the nodes by doing active power curtailment. Finally, for every run a curtailment value will be obtained. Once all the runs have been completed, a distribution of curtailment values will be obtained.

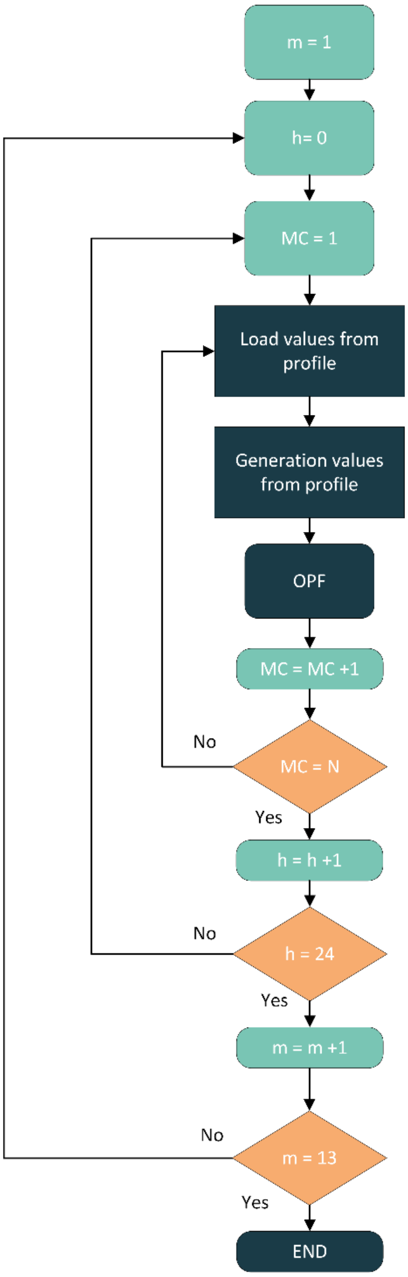

Fig 3: Model Flowchart

A. Model Output

In each of the Monte Carlo simulations a curtailment value will be obtained.

The sum of all curtailment values will form a distribution, as long as curtailment occurs in any scenario, otherwise there will be no distribution and there will be no curtailment risk.

Assuming that there is curtailment after running the simulations, three values will be obtained from the curtailment distribution, the Risk Value, the Conditonal Curtailment at Risk (CCaR) and the Curtailed Energy Percentage.

B. Risk Analysis

The aim is to provide a series of values in the output that study the risk involved in the operation that the investor wishes to carry out.

The conditional value at risk (CVaR) has been chosen as the parameter for measuring investment risk. This parameter is widely used in financial environments, specifically in the evaluation of the risk associated with investments in financial assets, usually portfolios, stocks, indices... However, it can be studied in other areas, as demonstrated in [15], [16]. In summary, the objective of the parameter is to evaluate risk scenarios to see if the losses in the event that these scenarios occur outweigh the gains.

As can be seen in Fig 4, the VaR returns a value of losses associated with a probability of this situation occurring, whereas the CVaR is more towards the tail of the distribution, being this the value of the mean of the area of the distribution that lies in the probability interval 1- α.

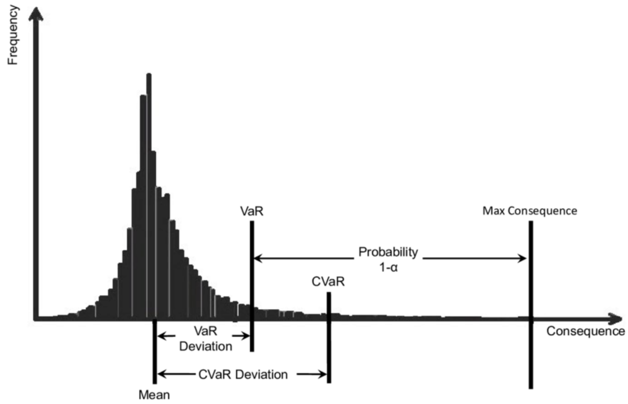

Fig 4: Conditional Value at Risk graphic representation, Source:[15]

1) Risk Value

Risk value in this project is determined as the percentage of hours that curtailment will occur. This is calculated following equation (2).

$$Risk\ Value = \frac{hours\ curtailed}{total\ simulated\ hours} \times 100 \qquad (2)$$

The aim of this result is to return the value of 1-α from Fig 4, this will give the investor information about how much curtailment time should be expected.

2) Conditional Curtailment at Risk

Conditional Value at Risk (CVaR) will be renamed, giving birth to the term Conditional Curtailment at Risk (CCaR). To calculate the CCaR value it is first necessary to know the value 1-α from Fig 4, which is the Risk Value. Once this value is established, the CCaR is determined by averaging the area enclosed inside the 1-α area, as equation (3) suggests:

$$CCaR = \frac{\sum Energy\ Curtailed}{\sum curtailment\ hours} \qquad (3)$$

This value reports the average curtailed power when the DER installation undergoes curtailment.

3) Curtailed Energy Percentage

The percentage of energy that has not been supplied is returned. This value has the aim of enabling the possibility of extrapolating this percentage to the annual production analysis, so that the investor, besides knowing the percentage of hours that will be curtailed, will also know the percentage of energy that it has not been able to supply allowing him to carry more detailed investment analysis.

$$CEP = \frac{\sum Energy\ Curtailed}{\sum Maximum\ produced\ energy} \quad (4)$$

IV. Test System

A. Grid

The network used is presented in the Matpower manual [17], it is a medium voltage distribution network, with a radial configuration and 17 nodes used in the IEEE, [18]. The configuration of the distribution network is shown in Fig 5. The entire study of the method proposed in this project will be carried out on this network.

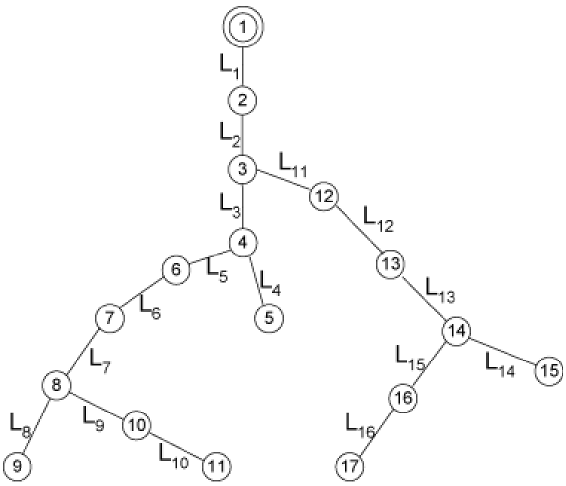

Fig 5: IEEE 17 bus distribution network

B. Input data

1) Load data

Starting from thirteen nodal demand profiles provided to Minsait by one of its clients, to generate a demand profile equivalent to six years and a half, from January 1st, 2016, up to July 31st 2022, this path was followed.

After gathering all the demand profiles, reference [19] was consulted to know the average consumption of each month.

Once the average consumption values are known, a multiplier was created for every month. As the year's mean value is 270 kWh, according to [19], [20], those months with an average consumption of 270 kWh have a multiplier of 1. The multiplier is obtained dividing the average month consumption between the year's mean consumption.

Then, each of the profiles is multiplied by a random normal distribution with the multiplier as a mean value and with a standard deviation of 0.2 to reduce significantly the probability of having a negative value.

Once this process is completed the resulting distribution will look approximately like Fig 6. Each node load will have its own distribution.

With the objective of modelling load uncertainty, for each Monte Carlo run, a random sample will be selected, in function of the month and the hour of the day that is under evaluation in that moment.

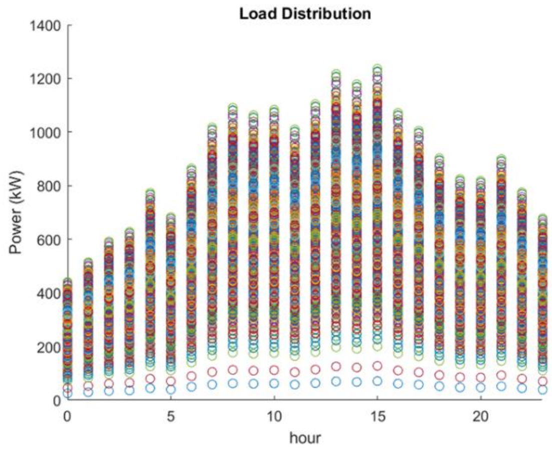

Fig 6: Artificial historical demand profile

2) Generation data

Meteorological historical measurements from the Military Base of Torrejón de Ardoz, Madrid, have been collected from NASA Power data access viewer web page [21], to estimate the amount of generation that can be injected into the grid under such circumstances.

To estimate the power that a PV installation will be able to deliver the values of the solar irradiance (in W/m2), from January 1st, 2016, up to December 31st, 2021, have been downloaded. Once processed, the historical profile obtained is represented in Fig 7.

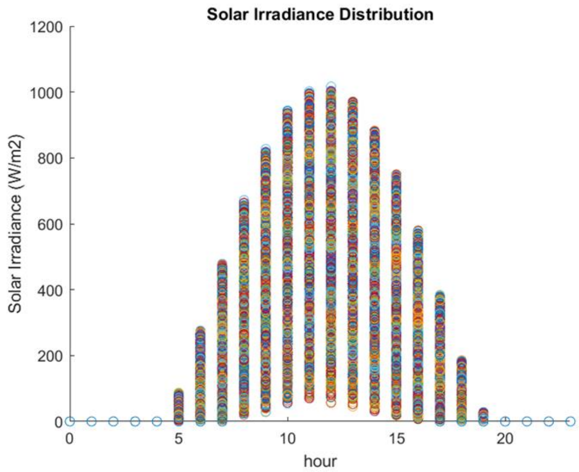

Fig 7: Historical (2016-2022) Irradiance Measurements

The same process has been carried out to obtain the historical measurements of the wind speed at 10 meters of height. The historical profile is represented in Fig 8, where each hour of the day has the number of samples corresponding to six years of measurements.

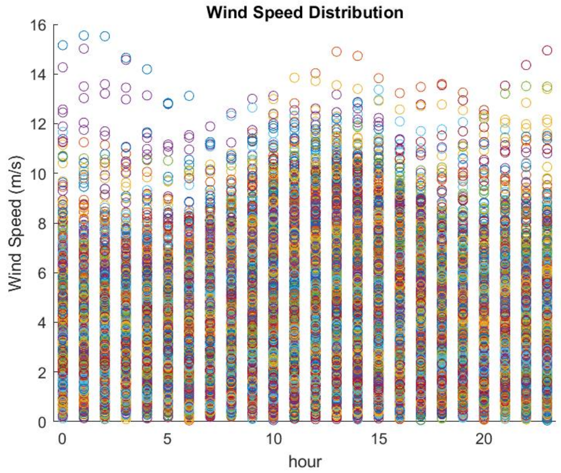

Fig 8: Historical (2016-2022) Measurements of Wind Speed at 10 meters

The model will sample a random value for both meteorological conditions measurements. These measurements will return a generation value that will be proportional to the installed power. The generation values will be introduced into the algorithm for the OPF to run.

V. Simulation Results Analysis

This section presents the results obtained from running the algorithm. Firstly, the algorithm output of a 6MW PV installation will be analysed. Afterwards, a comparison between four different HC calculation approaches will be made, the Curtailed Energy Curtailed, the Risk Value and the CCaR of these four methods will be discussed. In third place, the results from different installed capacities will be commented, these installed capacities have been simulated for a PV installation, a wind farm and a hybrid installation. Finally, as the curtailment results have been arranged to keep time data (month and hour), they will be broken down into an hourly analysis. The four algorithms to be studied are the following:

1. Worst Case scenario: as mentioned in previously, it selects the meteorological measurement that maximises generation and the minimum load recorded from the entire historical database, then, the OPF is executed. This is the traditional Hosting Capacity evaluation method and the one the project aims to improve.
2. The Hourly Worst Case scenario: selects the maximum generation at and the minimum loads for each hour, then it executes the OPF.
3. The Monte-Carlo based OPF considering only load uncertainty: picks the maximum hourly generation and a random value from the load distribution for each Monte Carlo run. This is also known as DHC with load uncertainty. This is the first of the algorithms proposed in the model, it is based on the algorithm proposed in [10], but the demand values are sampled in an hourly basis.
4. Monte Carlo based OPF considering both, load and generation uncertainty: picks random values for each hour out of the historical database. This is also known as DHC with generation and load uncertainty. This algorithm is the one to become the first approach towards the Onesait DERMS module and is the second algorithm to be proposed in this project.

A. *Output Results Analysis*

To determine the values of the CCaR, the Risk Value and the Curtailed Energy Percentage, the algorithm generates distributions which are represented in Fig 9 below, it shows the results obtained after simulating a 6 MW PV installation at node 9, for the DHC case considering generation and demand uncertainties.

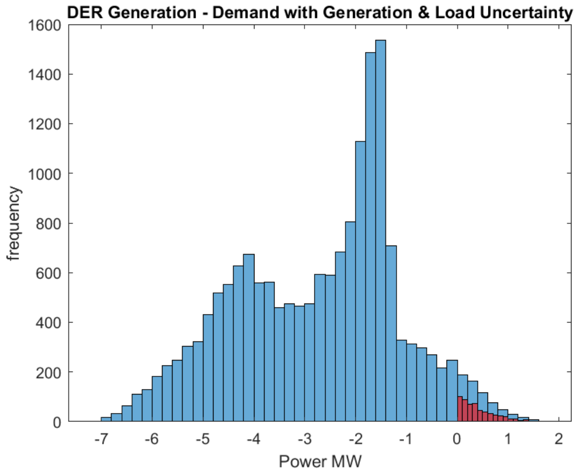

Fig 9: 6MW PV Installation Curtailment Distribution

Equations (2),(3) and (4) described in section III are applied to the simulated curtailement distributions to obtain the Risk Value, CCaR and Energy Curtailed Percentage values. Fig 9 represents the maximum available DER generation minus demand distribution in blue, and the curtailment distribution in red.

To begin, the curtailment distribution doesn't meet the positive tail of the generation minus demand distribution, this was expected, and demonstrates graphically the difference between a Power Flow and an OPF.

The parameters obtained from this distribution analysis are:

- Risk Value = 3.22%
- CCaR = 0.41 MW
- Curtailed Energy Percentage = 1.33%

The Risk Value will be variable, and it will depend on the distribution, the more hours that there is curtailment, the higher the Risk Value. Contrary to the traditional way of carrying out a CVaR based risk analysis, the (1- α) value is set by curtailment output distribution, highlighted in red in Fig 9, and not by the user. Then, the CCaR and the Curtailed Energy Percentage will be determined from the entire curtailment distribution.

B. *Comparison between Models*

Four calculation methods have been compared, these are: Worst Case scenario, Hourly Worst Case scenario, DHC with load uncertainty, DHC with generation and load uncertainty.

Having these methods defined, the results out of the simulation will be compared to evaluate if the performance of the proposed algorithm, the results under evaluation will be the Curtailed Energy Percentage, the risk value and the CCaR. All the results have been simulated under the same conditions: a 6 MW PV installation located in node 9 of the grid.

To begin, Fig 10 shows the Curtailed Energy Percentage. As it can be observed, if the 6 MW installation was evaluated using a Worst Case scenario approach, 97.06% of the energy produced will be expected to be curtailed. This result improves if an hourly Worst Case scenario is considered, the improvement is above 10% and results in 86.71% of the energy expected to be curtailed. Despite this improvement, the result could difficultly encourage the investor to carry on with his project, leaving him with the options of either reconsidering the size of the plant or abandoning the investment. When DHC methodologies are introduced, the results improve significantly, being the expected energy curtailment 4.74% in a DHC considering load uncertainty, and 1.33% if load and generation uncertainty are considered.

These results where expected as the worst case approaches don't take into account seasonality, which means that, in the case of the hourly Worst Case scenario, a generation in July could be compared with a demand from March. Therefore, the results are conservative values which are highly unlikely to occur. On the other hand, DHC methodologies are considering the temporality of the database resulting in more likely scenarios which offer a more realistic forecast.

Summarising, the proposed method is the most effective, the expected energy percentage to be curtailed has a value most encouraging for investors, the downside of this method is the computational burden, as it considers two uncertain variables.

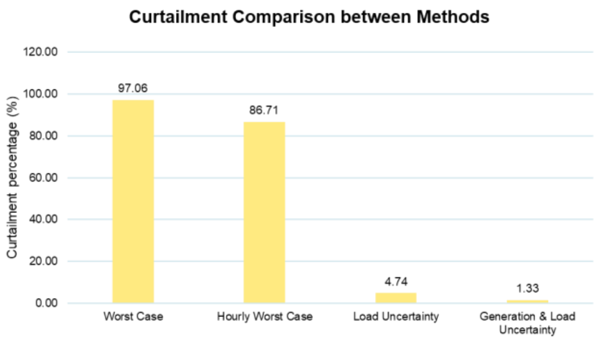

Fig 10: Curtailed Energy Percentage comparison between methods

Moving on to the Risk Value analysis, as it can be seen in Fig 11, the worst case approaches don't have a value for this indicator, this happens because these methods are deterministic and only return one value as an answer. On the other hand, the DHC approaches return distributions and from these, as shown in Fig 9, the Risk Value is calculated using equation (2).

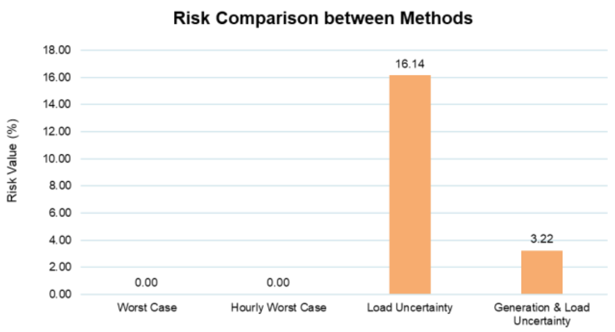

Fig 11: Risk Value comparison between methods

Looking at Fig 11, DHC considering generation and load uncertainty returns a Risk Value much lower than the Risk Value obtained from the DHC that only considers load uncertainty, 3.22% against 16.14% respectively.

Again, this was expected, as the DHC approach with just load uncertainty takes the maximum hourly generation, where, for example, in winter months, such generation values will be highly unlikely to take place.

With the analysis of the CCaR happens the same thing as with the analysis of the Risk Value, as the worst case approaches are deterministic methods, there is no distribution to obtain the CCaR from.

Fig 12 portraits the CCaR results from the simulation, in this case the values are very similar, still the DHC with load and generation uncertainty outperforms DHC with just load uncertainty, CCaR of 0.41 MW for the former and CCaR of 0.57 MW for the latter.

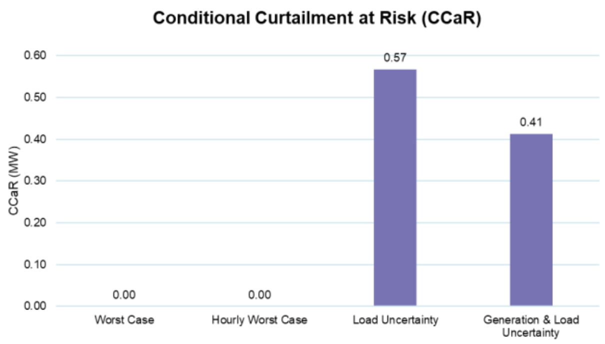

Fig 12: Conditional Curtailment at Risk comparison between methods

The CCaR result from Fig 12 jointly with the Risk Value result from Fig 11 states the following:

- DHC with load uncertainty approach has a Risk Value of 16.14% and a CCaR of 0.57 MW. This implies that the investor can estimate that his plant will suffer curtailment for 16.14% of hours and the mean power that will be curtailed during those hours will be 0.57 MW.
- DHC with load and generation uncertainty has a Risk Value of 3.22% and a CCaR of 0.41 MW. This implies that the investor can estimate that his plant will undergo curtailment 3.22% of the time during a

year, and the mean curtailed power during that time would be 0.41 MW.

These outputs can be used to develop a flexible contract between the DSO and the investor, the contract could be confectioned so that there is a compromise between the interests of both parties, leaving room for the DSO to operate the plant and not jeopardizing the financial performance of the investment.

C. *Installation Performance when subjected to Installed Capacity Increments*

This section of the analysis of the results studies how the indicators (Risk Value, CCaR and Curtailed Energy Percentage) vary depending on the installed power and the type of technology being installed when running the DHC with load and generation uncertainty algorithm.

To carry out this analysis, the installed power was increased in steps of 0.5 MW from 2.5 to 7 MW and then two more simulations were carried out, one with an installed power of 8 MW and the other with an installed power of 15 MW. These have been simulated for PV, wind and hybrid installations, which are composed by both PV and wind.

Fig 13 shows how the technology that presents the least risk for lower installed powers is PV. Nevertheless, the increase in Risk Value that this technology suffers when the power exceeds certain thresholds is much more pronounced than with the rest of the technologies. This means that investors must be careful when designing their plants, as the risk of curtailment increases considerably with the power of the plant. On the other hand, wind power plants have a much more linear risk evolution than PV plants. Finally, the best performing technology in terms of risk value is the hybrid technology. It has barely risk until the 15 MW plant is simulated, there is a change in the risk trend from 8 MW to 15 MW, this change in the trend may be due to the presence of photovoltaic installations, as the risk of these installations is very sensitive to the installed power, which can produce the same effect in hybrid installations.

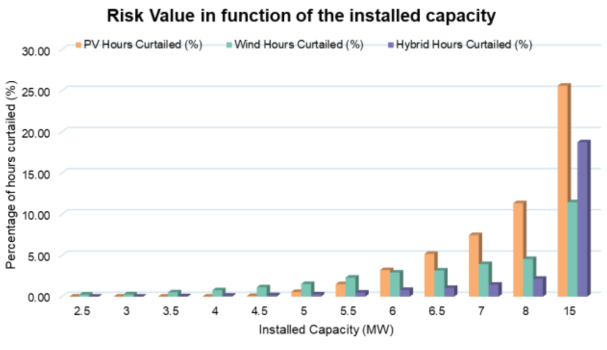

Fig 13: Risk Value in function of the installed power

The study of the evolution of CCaR as a function of installed power is shown in Fig 14. Once again, the value of CCaR increases as installed power increases. As in the case of the Risk Value, the technology that seems to be more sensitive to the installed power is PV. Despite this, it presents the lowest values from 2.5 MW to 7 MW of installed power. This implies that when the photovoltaic installation is undergoing curtailment, on average, the power that is not being supplied will be lower than in the rest of the technologies. Talking about the CCaR of wind installations, these present the highest CCaR values for all installed power except for 15 MW, which implies that although the Risk Value is lower, on average, the power that is not being supplied will be high, for example, for an installed power of 2. 5 MW of wind power, the CCaR value is 0.41 MW, which means that on average, when curtailment occurs, 16.4% of the power that is being generated in the plant at that moment will not be injected. To conclude with the CCaR, the hybrid installation is the one with the lowest sensitivity to the installed power, and its performance at low installed powers is close to the values of the PV installation.

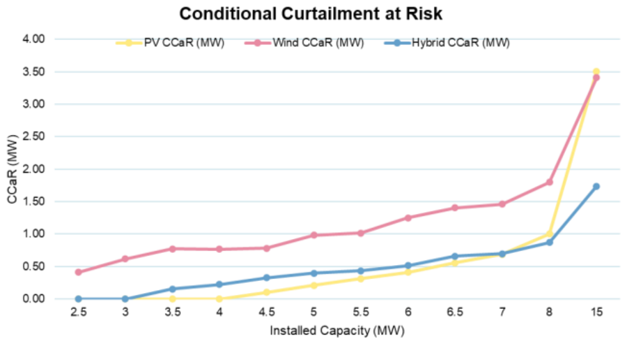

Fig 14: CCaR evolution in function of the installed power

The third and last parameter analysed is the Curtailed Energy Percentage, which is shown in Fig 15. The pattern is very similar to that of the CCaR, with the best performance in the overall calculation being that of the hybrid installation, which shows the least sensitivity to installed power, except at high power levels, where the slope of the hybrid installation is steeper than that of the wind installation. The progression of the indicator in PV installations also shows satisfactory results, again this technology is very sensitive to the installed power, however, up to 7 MW installed, the Curtailed Energy Percentage does not exceed 5%, which implies that with an installation of 7 MW, over the course of a year, the energy not supplied will be less than 5%. The correlation of this indicator with the CCaR in a wind farm is very high, the Curtailed Energy Percentage is the highest in all cases with the exception of 15 MW. In installations of this type, it would be appropriate to install less power, for example, if a threshold of 5% is established, the wind installation would have to be 5.5 MW.

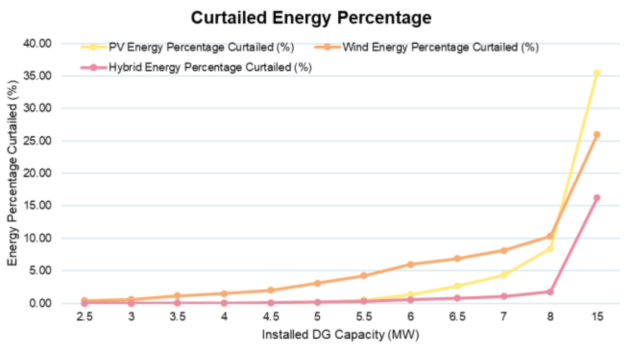

Fig 15 Energy Percentage Curtailed in function of the installed power

In summary, as mentioned above, all three indicators increase with installed power. The points to be drawn from the analysis are as follows:

- For lower plant installed power, based on the indicators alone, the best choice is photovoltaics.
- In the overall calculation, the best choice is a hybrid installation, however, the investment costs would have to be studied to see if it is profitable or not.
- Wind installations in the area where the simulations have been carried out are again, in view of the indicators, the worst choice among the three options presented.

D. Curtailment Time Analysis

One of the strengths of the proposed methodology is that hourly discrimination is retained, this may also be an output of the algorithm which aims to give more information to the investor so that it can assess the investment more accurately. The need to return these results to the investor arises from the variation in the price of energy over time, since curtailment impact during peak hours is not the same as curtailment impact during flat or off-peak hours.

The analysis is the same as in the previous section, the algorithm will obtain the result of the three indicators, the Risk Value, the CCaR and the Curtailed Energy Percentage, for each hour.

After the simulation of the 6 MW PV plant, the results are shown in Fig 16 and Fig 17. As it is a photovoltaic plant, it makes sense that the curtailment takes place in the intermediate hours of the day, in this case, from 9:00 to 16:00.

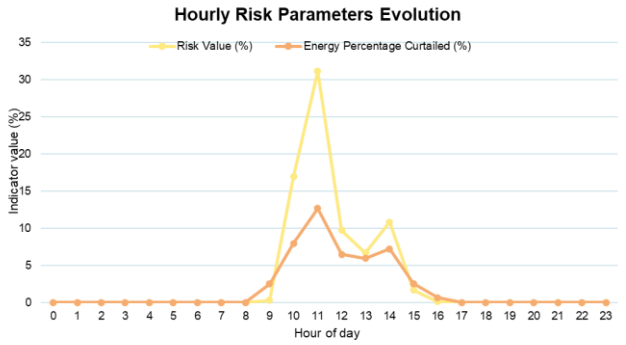

Fig 16: Risk Value and Curtailed Energy Percentage hourly evolution

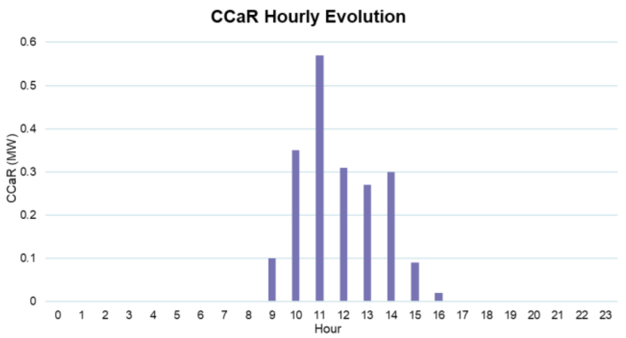

Fig 17: CCaR hourly evolution

Analysing the patterns from Fig 16 and Fig 17, a 6 MW installation is estimated to suffer curtailment approximately eight hours of the day. The hour with the highest risk of curtailment is 11:00, where the Risk Value takes a value close 31%, at this hour also coincides with the CCaR and Energy Percentage Curtailed values taking the highest values of the whole day, 0.57 MW and 12.67% respectively. The next most curtailment-prone hours are 10:00 and 14:00.

Temporal analysis is another tool to facilitate the study of investments in distributed generation in the distribution network, it can simplify the work in the design phases of the DER installation as well as in the economic projections that are made to value an investment.

VI. Conclusions

It has been demonstrated that by including the uncertainties associated with generation and demand in the algorithm, and performing a Monte Carlo based OPF analysis to model them, the Hosting Capacity increases considerably. Concretely, the energy curtailed improved in more than 95% with respect to the Worst Case Scenario when running the DHC algorithm considering generation and demand uncertainties. Achieving the goal of improving the conservative model has been achieved.

Furthermore, another observation made after comparing the performance of the different methodologies is that the DHC with uncertainty in demand and generation, performs better than the DHC with uncertainty in demand; thus, the results obtained with the latter methodology are acceptable, as it improves the results obtained with the Worst Case Approach by 92%.

Although the results are better when considering generation and demand uncertainty. When to make a flexible contract, it would be beneficial to see the results of both DHC methodologies to elaborate it, with the objective of giving more flexibility to the DSO operation by establishing looser contract terms, such as something intermediate between the result considering only demand uncertainty and the result considering demand and generation.

To determine the size of the DER installation, Risk Analysis, CCaR and Curtailed Energy Percentage are the three parameters to analyse. Moreover, there is a possibility to analyse graphically the design of the plant by watching the probability distributions produced by the algorithm.

Regarding the graphic analysis, for photovoltaic installations, one of the indicators of over dimensioning is the analysis of the shape of the curtailment distribution, in the event that the shape of the distribution flattens out, it is an indicator that the installation is over dimensioned. For hybrid and wind turbines, the shape does not tell us as much, as they tend to be always convex. In these two cases looking at the limits of the graph will be more representative. If the curtailment registers are similar to the installed power on some occasions, it is an indicator that the installation may be over-dimensioned.

With regard to the numerical analysis. Photovoltaic plants present a lower risk up to a certain installed capacity. This is due to the sensitivity of the indicators to increases in installed power, which is why it is necessary for them to be correctly designed. In the case of oversizing, the investment will worsen, and the returns will not be as profitable. Hybrid plants show the best results and the best response to power increase, for these installations the risk of oversizing is not as high as in a PV installation, however, the initial investment would have to be assessed to see the profitability. Finally, wind installations are the worst performers in terms of Curtailed Energy Percentage and CCaR.

When making decisions, it is important to look at the three indicators, and not to look only at one of them to assess whether the investment is a good one or not.

Speaking about the hourly breakdown, it gives the possibility to adjust the plant dimension to minimise curtailment when prices are high. Time analysis is significant in time-of-day sensitive DER technologies, it can help in the design of the DER installations and in the economic analysis of the investment.

Finally, after the analysis of the results, it has been concluded that the outputs of the algorithm should be used to develop a flexible contract that satisfies all interested parties. To this end, it is proposed to establish contractual limits that are slightly higher than those obtained after running the algorithm, which give the DSO room for manoeuvre if necessary, and which do not harm the economic performance of the installation. As mentioned, one of the proposals would be to establish the contract conditions at an intermediate point between the results obtained in the DHC simulation with only demand uncertainty and DHC considering generation and demand uncertainties.

VII. Future Works

In view of the project carried out, the following lines of research are proposed, which may lead to possible future works.

To begin, one of the immediate jobs would be to modify the inverter control, right now the control is a VWOM active power control, as it reduces the active power injections to control the voltages at the nodes. A possible improvement would be to introduce a VVWOM control, which combines active and reactive power control, and see how this control would improve the inverter indicators.

The next proposed future work is to consider the evolution of the HC over time. The value of the HC is not static as it varies according to the demand in the network. A valuable contribution would be, using Artificial Intelligence techniques, to include in the algorithm a prediction of the evolution of demand in the coming years. This would provide investors with information on the performance of their installation in the following years. Which could allow them to consider installing more power in the present, even if the indicators are not so favourable, in the knowledge that in the future these indicators will improve. This will also allow the investor to negotiate a flexible contract with the DSO, agreeing to higher curtailment in the present in exchange for lower curtailment in the future, as energy demand increases.

In addition to the above, the study of the evolution of weather conditions over time, using Artificial Intelligence techniques can also be included. Due to climate change, the parameters may evolve, which means that the projections made a priori may deviate from reality and the flexible contracts established between the DSO and the owner of the installation may not be fulfilled.

Another future work is the development of flexible contracts, this would entail a process of studying the regulation in the connection zone, once the regulation has been studied, the flexible contract would aim to establish an agreement between the DSO and the owner of the DER installation, where the operating conditions are agreed. These conditions will be based on the indicators resulting from the algorithm. For example, assuming that the Risk Value takes a value of 10% and the Curtailed Energy Percentage takes a value of 7%, the contract could dictate that such a DER installation can be controlled (can undergo curtailment) by the DSO at zero cost until either the value (in percentage) of non-supplied energy reaches 7%, or the number of hours with curtailment reaches 10%, if these values are exceeded, the owner of the DER installation will have to be compensated. This implies that for the DER installation under review, the cost function will have to be modelled to represent these offsets in the system costs.

The current algorithm is designed for a grid with no DER connected, elaborating a complex cost function that models the flexible contract of each DER installation will be necessary to assess the incursion of future DER technologies into the distribution network. Therefore, the algorithm will help with the creation of new DER flexible contracts by considering the previous flexible contracts.

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