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Hosting Capacity Methods Considering Complementarity between Solar and Wind Power

– A Case Study on a Swedish Regional Grid

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Although the work has been challenging and required many coffee breaks, it has been really enjoyable! During the course of this work, Mahmoud reminded us of some encouraging words:

"All models are wrong, but some are useful." – George E.P. Box

Abstract

The demand for electrical power is growing due to factors such as population growth, urbanisation, and the transition from fossil fuels to renewable energy sources. To be able to keep up with the changes in electricity demand, the Swedish power grid must connect more renewable power generation, but also increase its transmission capacity. Traditionally, power grids are expanded to increase the transmission capacity which requires a lot of time and investments. In order not to hinder the electrification of society, it is important to adequately estimate the current transmission capacity and plan the expansions accordingly. In the past, the generation of electrical power was primarily based on dispatchable energy sources, and the planning of new connections to the grid was assessed according to the stable and controllable nature of the electricity supply. However, renewable sources like solar and wind power are affected by weather variations. Therefore, the traditional methods of planning the power grid are no longer sufficient. Instead, there is a need to develop and implement new methods that account for the variable nature of renewable energy sources, and also the possible complementarity between different renewable power sources. This can possibly allow more connection of renewable power generation to the grid, without the need of expanding it.

The aim of this thesis is to investigate two different methods for analysing how much renewable power generation that can be connected to the power grid, so-called hosting capacity methods. The first method is a deterministic method which is traditionally used in power system analyses since it is a fast, simple and conservative method. This method does neither consider the intermittent nature of solar and wind power, nor any complementarity. The second method is a time series method which considers the complementarity and intermittency of solar and wind power but requires much data. The methods are compared in regards to assessed hosting capacities, risks and reliability of results.

The study is performed on a regional grid case in the middle of Sweden. Solar and wind power plants with different capacities are modeled at ten buses in the power grid. The power grid is analysed in PSS/E with loading of lines and voltage levels determining the assessed hosting capacities. A correlation map presenting the temporal correlations of solar and wind power over the grid case area is also created in order to evaluate the complementarity in the area and its possible effects on the assessed hosting capacities.

The results show that the time series method is more reliable than the deterministic method. This is due to the difficulties in identifying accurate worst case hours that are used for the deterministic method. The time series method is also preferred as it considers complementarity between solar and wind power. However, the correlation map argues that the grid case area has weakly positive correlations, meaning low complementarity between solar and wind power. This suggests that the differences in hosting capacity between the two methods are more likely dependent on the temporal variations in existing load and power generation. The differences in assessed hosting capacity between the ten buses in the power grid are probably not due to the local complementarity either, but rather the structural differences of the grid in terms of components, local loads and existing power generation.

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Glossary

Bus is the name of the nodes in the power system. It is where components like generators, loads, and power lines are connected.

Complementarity is a relationship in which two or more entities improve or emphasize each other's qualities. Concerning renewable power generation, high complementarity is coupled with strong negative correlations between the two renewable energy sources. A correlation coefficient of 1 indicates no complementarity.

Correlation describes the relationship between two variables, meaning to which extent two variables are linearly related, without making a statement about effect or cause. The correlation coefficient is between 1 and -1. A positive correlation means that the variables change in the same direction, and a negative correlation means that they change in the opposite direction.

Curtailement is an action to reduce the amount of power generated (usually from a renewable resource) to be able to maintain a balance between supply and demand, due to limits in the power grid or for economic reasons.

DLR is an acronym for Dynamic Line Rating. It is a technique which provides information on the actual capacity of a power line at any given moment. The actual capacity is dependent on the ambient conditions.

DSO is an acronym for Distribution System Operator. It refers to a company owning the distribution grid and being responsible for distributing and managing electricity from power sources to end customers.

Hybrid generation refers to the generation of solar power and wind power at the same location.

Load refers to the amount of power from the power grid that is consumed by the end customers.

Loading refers to the amount of current passing through a power line in relation to its maximum capacity.

Overloading refers to an excessive amount of current passing through a power line. The power flow is exceeding the maximum capacity of the power line.

TSO is an acronym for Transmission System Operator. It refers to an entity or organisation responsible for controlling, operating and maintaining the transmission grid.

1 Introduction

The demand for electricity is increasing globally and within Sweden due to factors such as urbanisation, population growth, automation, and the electrification of industries. In a digitalised world, an increasing number of sectors are dependent on a secure supply of electricity [1] [2]. At the same time, electricity demand is constantly growing in order to transition from fossil fuels to an energy system with net zero greenhouse gas emissions [2] [3]. This implies an increased usage of electrical power generated from intermittent renewable energy sources, as well as the need to improve the transmission capacity of the grid. Traditionally, to meet an increased capacity need, the power grid is expanded. However, power system expansion takes time. In Sweden, an overhead power line of a regional grid takes about 3–5 years to complete, and an overhead power line of a transmission grid takes about 10–15 years [1]. In order to not waste critical time in the electrification process, it is important to adequately assess the grid capacity to make accurate planning of expansion needs.

There are two categories of power grids: transmission grid and distribution grid [4]. In Sweden, the distribution grid is further divided into the regional and local grid. The regional grid connects the transmission grid to the local grid. Large electricity consumers and medium-sized power generators are often directly connected to the regional grid. The transmission grid usually maintains a voltage level between 220 and 400 kV, the regional grid between 20 and 130 kV, and the local grid between 0.4 and 20 kV. The majority of the Swedish regional grids are owned by the Distribution System Operators (DSOs) E.ON Elnät Sverige, Vattenfall Eldistribution and Ellevio [4]. This thesis is based on a regional grid case given by Ellevio and the general focus of the study will be regional grids in a Swedish context.

Research has shown that negative correlations between solar and wind weather conditions and power generation can occur [5] [6]. Negative correlations indicate that when there is high solar power generation, there is low wind power generation, and vice versa. This means that when solar and wind power are installed, the highest possible power generation from both of them rarely occurs at the same time [6]. However, when estimating the grid capacity in order to accept more power generation, the highest possible power generation is often assumed [7], which equals the sum of installed capacities. This has worked for traditional, dispatchable power sources [8]. However, in today's evolving power system it might result in the amount of renewable energy that could be connected to the grid being underestimated [7].

It is the transmission system operator (TSO) and DSOs owning the grid which decide on whether it is feasible to accept more connections of power generation or not. Accepting generation from a renewable, intermittent energy source can lead to various problems for the grid, which must be addressed and investigated in beforehand. A common way to do this is to analyse the hosting capacity. The hosting capacity of renewable energy sources in a power system is a limit of how much renewable power generation can be connected to the power system with the system still being reliable and secure [9], without expanding the grid. The hosting capacity is decided by different performance indices of the power system and their limits [7]. Estimating the hosting capacity can be accomplished using many different methods. These can be grouped into three main approaches: deterministic, probabilistic and time series methods [7]. The common way is to use a deterministic method when analysing the power system and its connections. The deterministic method does neither consider the intermittent nature of solar and wind power, nor does it consider any correlations between for example power generation and load or between power sources [7]. Alternative methods to the deterministic might allow more renewable power generation in the power systems and are therefore important to investigate.

1.1 Aim

The aim of this study is to compare different hosting capacity methods in regard to their resulting hosting capacity and related risks. The hosting capacity methods are to be highlighted from a perspective where the complementarity of renewable energy sources is taken into account. The reliability of the hosting capacity methods is also discussed.

1.1.1 Research Questions

The following research questions are to be studied and answered in this thesis.

- How do the assessed hosting capacities differ between different hosting capacity methods?
- How does the complementarity between solar and wind power in the area affect the assessed hosting capacities?
- What risks do these methods involve concerning the thermal loading of lines and voltage variations?

1.1.2 Limitations

This study is focusing on regional grids in a Swedish context. The grid case provided by Ellevio is limited to fit the 50-bus limitations of PSS/E. The case is limited geographically to an area in the middle-southern part of Sweden. The power generation and load data are from the year 2020, and they remain unchanged in the different scenario simulations, meaning no possible changes in already existing power generation or load are considered. Furthermore, possible future changes to the grid structure in the case are also not considered. Regarding so-called power quality, only active effects and voltage levels are considered in the power system analyses. The power system analyses are performed under steady-state conditions. Moreover, the fulfilment of so-called network codes, in other words, regulatory limitations regarding the power system and its connections, is not covered by this thesis.

1.2 Previous Research

The impact of hosting capacity methods for accepting more renewable power generation has been discussed in previous research from different points of view. Liebenau et al. [6] performed a cluster analysis on different areas of Germany where combined cumulative probabilities were calculated for solar and wind power generation at various sites in the areas. The writers concluded that there is no need for planning the power system based on maximum generation from both power sources at the same time as this never occurs in their examples, but also that the difference from maximum generation is not the same for all places which indicates that analyses must be performed for all locations. The writers could also see that planned power grid expansion of transmission lines could be reduced with this method, however, this also required some curtailment in their simulations. In the study, no possible risks for the power system were observed as curtailment was instead assumed.

Sun et al. [10] evaluated the connection of hybrid generation of solar and wind power to a UK generic distribution grid placed in Scotland, using optimal AC power flow analyses. The complementarity between wind power, solar power and load respectively was also examined by calculating how many hours during a year certain levels of power generation and load were reached at the same time. The study concluded that the power grid was more efficiently used

and hosting capacity was increased with hybrid generation of solar and wind power compared with a single resource generation. This effect was strongly enhanced using different ways of active power system management, for example, curtailment. The authors also concluded that up until now, little research has been done to examine the effects over a power system and its capacity in regard to integrating hybrid generation.

Le Baut et al. [11] evaluated different methods to enhance the hosting capacity of a medium voltage grid using probabilistic analysis. However, all the methods included smart grid technology and thus the report was not focused on how the hosting capacity might be underestimated today, but rather on how different technologies could increase it.

Jansson et al. [12] developed a probabilistic method for power flow calculations, in cooperation with a Swedish DSO. The method was tested for different applications, for example, to assess hosting capacity for wind power. Risk assessment for the components of the power grid or interpretation and analyses of the results from the method were not conducted.

The correlation and complementarity between solar and wind power have been investigated before in several research contributions. For example in a Nordic context, Widén et al. [5], Olauson et al. [13] and Lindberg et al. [14] covered this, of which Olauson et al. also included load. The spatial correlations of wind power in a Nordic context were examined by Holttinen et al. [15] and Widén et al., where Widén et al. also looked into spatial correlations of solar power and a combination of solar and wind power. Outside of the Nordic context, several papers have investigated correlations between renewable energies and, in some cases, load. Some examples are Hart et al. [16], Pennock et al. [17] and Wang et al. [18]. A literature review of different ways to assess the complementarity between renewable energy sources is found in Jurasz et al. [19], which also highlighted the need for more research on assessing the complementarity between solar and wind power when planning the future power system.

A literature review on different methods to analyse the hosting capacity, including their advantages, drawbacks and possible applications, is found in Mulenga et al. [7]. The paper highlights a current research gap between the scientific approach to the different methods and their practical application by DSOs.

This thesis aims to fill this gap by being carried out in close cooperation with a DSO. To the best of our notice, no paper has evaluated different methods of assessing hosting capacity using power flow analysis on a case from a DSO, assessing risks for thermal overloading of lines and unacceptable voltage variations, while taking complementarity between different renewable energy sources into account.

2 Theory

The following sections summarise relevant theory concerning solar and wind power, correlations and complementarity between renewable power generation and load, the regional grid and power system analysis.

2.1 Wind Power Characteristics

A wind turbine converts energy in the wind to electrical power [20]. The conversion process uses the basic aerodynamic force of lift to generate a net positive torque on a rotating shaft. This results in mechanical power generation which is transformed into electrical power using an electric generator. The most common design of wind turbines today is the horizontal axis wind turbine with upwind rotor orientation [20].

The power from a wind turbine varies with wind speed and every wind turbine has a characteristic power performance curve which presents the electrical power output as a function of the hub height wind speed [20]. Figure 1 presents a general power curve of a wind turbine. The power curve makes it possible to predict the power generation of the wind turbine without taking the technical details of the components into consideration. There are three key points on the velocity scale: the cut-in wind speed, which is the speed at which the turbine starts to generate electricity; the rated wind speed, which is the speed at which the turbine generates its maximum power output; and the cut-out wind speed, which is when a braking mechanism is activated to stop the wind turbine before it risks getting damage [20].

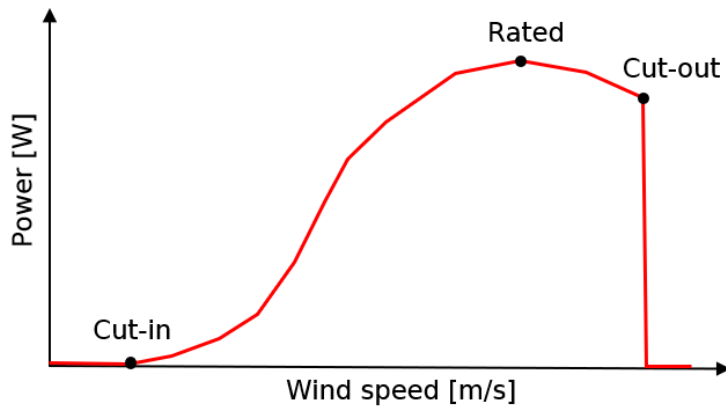


Figure 1: A general power curve of a wind turbine inspired by Manwell et al. [20].

The capacity factor is the average energy output from a power plant during a period of time divided by the energy output that would have been generated if the power plant was generating at installed capacity during the same period of time [21] [22]. The worldwide average capacity factor for on-shore wind power plants was 38.8% in 2021 [23]. For comparison, in the middle-southern part of Sweden (SE3) the installed wind capacity was 3 279 MW and the yearly generation was 7 969 GWh in 2021, resulting in a capacity factor of 27.7% [24].

2.1.1 Wind Speed Variation with Height

Wind speed varies with height, and there are different ways to extrapolate wind speed from one height to another. Among these are Deacon's law, the logarithmic law, and the power law [25]. In wind energy studies, the logarithmic law and the power law are the most common mathematical models used [20]. Both approaches have uncertainties due to the variable, complex nature of turbulent flows. The logarithmic law can be predicted and derived in a number of ways, one of which is

$$U(z)/U(z_r) = \ln\left(\frac{z}{z_0}\right) / \ln\left(\frac{z_r}{z_0}\right), \quad (1)$$

where $U(z)$ [m/s] is the wind speed at height z [m], $U(z_r)$ [m/s] is the wind speed at the reference height z_r [m], and z_0 [m] is the surface roughness length which characterises the roughness of the ground terrain. Table 1 presents various values of surface roughness length for different terrains [20].

Table 1: Surface roughness lengths for various types of terrain [20].

Terrain Description	z_0 [mm]
Very smooth, ice or mud	0.01
Calm open sea	0.20
Blown sea	0.50
Snow surface	3.00
Lawn grass	8.00
Rough pasture	10.00
Fallow field	30.00
Crops	50.00
Few trees	100.00
Many trees, hedges, few buildings	250.00
Forest and woodlands	500.00
Suburbs	1 500.00
Centres of cities with tall buildings	3 000.00

The power law represents a simpler model, which is

$$U(z)/U(z_r) = (z/z_r)^\alpha, \quad (2)$$

where α [-] is the power law exponent ($0 \leq \alpha \leq 1$) [20]. The power law exponent varies with parameters such as elevation, time of the day, nature of the terrain, season, wind speed and temperatures [20]. Assuming a constant value of the power law exponent may not be appropriate since it assumes that the surface roughness is constant which may not be accurate for all terrain types [25] [26]. Some researchers have developed methods for calculating the power law exponent from the parameters in the logarithmic law. However, many find that these complicated approximations reduce the applicability and simplicity of the power law, meaning that energy specialists should accept the empirical nature of the power law and choose values of α that best fit available wind data [20]. If the necessary information is unavailable, the value of $\alpha = 1/7$ is often used, but it should be noted that it can reduce the accuracy of the results [27].

2.2 Solar Power Characteristics

Solar power is generated from incoming solar irradiance. The sun radiates 3.845×10^{26} W, of which the irradiance reaching the atmosphere of the Earth is $1\,367$ W/m² [28]. Of this, approximately 61% is known as direct irradiance reaching the Earth, and this together with the

so-called diffuse irradiance forms the global irradiance of 1 000 W/m². The diffuse irradiance comes from the scattering of light in the atmosphere, and can for example be irradiance reflected by particles in the atmosphere [28].

Solar power is in this thesis referring to photovoltaics (PV). PV is the direct conversion of sunlight into electrical power using solar cells, which consist of semiconducting material [28]. Many solar cells are mounted together in a solar module, and several of those are in turn mounted together in a string and connected to an inverter. The inverter converts direct current to alternating current [28]. In order to improve the economics of solar power, the panels are often overdimensioned when compared to the capacity of the inverter [29]. This overdimensioning is denoted by the DC/AC ratio of the chosen inverter being higher than 1. Any solar power generation above the inverter capacity is curtailed, but the economic loss from the curtailment is compensated for by avoiding a higher power tariff, as the maximum capacity is decreased with a higher DC/AC ratio. A ratio of around 1.3 is found to be economically optimal in Sweden according to Westén [29]. A trend seen lately in for example Belgium, is to increase this ratio to around 1.3 from lower values around 1 [30].

Besides the DC/AC ratio, generated solar power from a system depends on several factors. Some significant of these are: the angle of incidence [31], spectral effects and temperature of the module [32] [31], and environmental impacts such as dust, soiling and shading [33].

The angle of incidence relates to that losses occur from the angle of solar irradiance not being coincident with the normal of the module. The spectral effects relate to the efficiency of the solar cells depending on the spectrum of the incoming solar irradiance. The temperature of the module also affects the efficiency, and has a greater impact than the angle of incidence and spectral effects [31] [32]. Dust and soiling can also affect efficiency, but this varies a lot with the site of the solar power system [33].

The capacity factor of a solar power plant is generally low due to low conversion efficiency. It usually varies between 15 and 35% [22]. The worldwide average capacity factor for utility-scale solar power systems during 2021 was 17.2% [23]. In Sweden, the average capacity factor is around 11%, which is derived from Lindahl et al. [34].

2.3 Correlations and Complementarity

Complementarity is a relationship or situation in which two or more entities improve or emphasize each other's qualities [19]. There are several metrics for assessing complementarity in a power system. Some examples are load tracking indices, ramp rate assessment, loss of load probability, correlation coefficients such as cross-correlation, and many others. The most used measure of dependence between two randomly distributed variables is correlation, and the most common metric for quantification of complementarity between renewable power sources is Pearson correlation. Pearson correlation coefficient can be used as a tool for the evaluation of renewable energy sources in order to configure an efficient power system, or improve the operation of such [19]. In this thesis, complementarity is assessed by calculating Pearson correlation coefficients, where high complementarity between solar and wind power is defined as strong negative correlation between the two renewable power sources.

The Pearson correlation coefficient for two data series $X(t)$ and $Y(t)$ is defined as

$$\rho_{X,Y} = \frac{\sum_t (X(t) - \bar{X}) (Y(t) - \bar{Y})}{\sqrt{\sum_t (X(t) - \bar{X})^2} \sqrt{\sum_t (Y(t) - \bar{Y})^2}}, \quad (3)$$

where \bar{X} and \bar{Y} are the mean values of the data series $X(t)$ and $Y(t)$ respectively, $t = 1, 2, \dots, N$ is the index for the data series of N indexes, and $\rho_{X,Y}$ is the correlation coefficient ranging from

-1 to 1 [5]. A negative correlation coefficient indicates that when one variable increases, the other variable decreases [35]. A positive correlation coefficient indicates that when one variable increases, the other variable also increases. A coefficient of 0 implies that there is no correlation between the variables. Correlation is a measure that can only be used for comparison and does not provide information on whether there is a cause for the seen behaviour, or if it is completely random [35].

Correlation can be divided into temporal, spatial and spatio-temporal. Temporal correlation in this context refers to the correlation between power sources at the same location. Spatial correlation refers to the correlation between dispersed power sources. Spatio-temporal is a combination of both [19].

It is important to understand how solar, wind and load complement each other in order to better utilise their different characteristics in power system analyses. Therefore, an overview of relevant correlation coefficients from the literature is presented. Comparing research from for example China performed by Wang et al. [18] and different regions in Great Britain performed by Pennock et al. [17], it is clear that the Pearson correlation coefficients vary between regions within a country and between countries over the world. The spread of correlation coefficients indicates the need for location-specific investigations. As the study in this thesis is based on a case in Sweden, the correlation coefficients from the Nordics are more relevant than those from other parts of the world. With this in mind, research from Sweden and the Nordics will here be presented.

2.3.1 Spatio-Temporal Correlations

Two articles are found that investigate spatio-temporal correlations between solar and wind power on a Swedish and Nordic scale respectively. Widén et al. [5] simulated a future scenario for Sweden and the correlation between total solar and wind power from the country was calculated over different time scales. This resulted in a correlation of -0.2 between the power sources on an hourly scale down to -0.74 on a monthly scale. Similar results are found in a paper covering the whole Nordic system, in a simulated possible future scenario [13]. Here, solar power and wind power show a strong negative correlation of around -0.75 on a long term perspective of more than four months, but a smaller positive correlation of around 0.07 on a short term perspective of less than two days.

In the same report covering the Nordic system, correlations to load were also investigated. It was shown that solar power has a strong negative correlation of around -0.8 to load in a long term perspective of more than four months, but a positive correlation of 0.42 on a short term perspective of less than two days. Wind power and load show a strong positive correlation of around 0.75 long term, but no correlation on short term [13].

2.3.2 Temporal Correlations

For purely temporal correlations of power sources at one site, the investigation of hybrid power generation is of interest. According to the modeling of several such Swedish sites, where solar and wind power generation is co-located, negative correlations are found on all time scales (hourly, diurnal, synoptic, mid-term and seasonal) but are biggest on the seasonal scale [14]. On an hourly scale, the correlations are around -0.1 to -0.2. The most negative correlations are found on the east coast and the southwestern coast of Sweden, while slightly positive correlations can be found in some of the more mountainous parts in the north of Sweden [14].

2.3.3 Spatial Correlations

If the distance between two renewable power plants increases, the correlation in power generation between them generally decreases [16]. The correlation coefficient depends on which power source it is and the actual distance, but also the terrain and the time scale.

Specifically for wind power, the spatial correlation seems to be around 0.9 for a distance of up to 10 km, then it decreases and reaches 0 for around 1 500 km, after which it might reach negative values [16]. Similar results are found by Widén et al. [5], stating that research around this is comprehensive and united in its conclusion that dispersion of wind power decreases the variability of the total wind power generation. The correlations amongst the wind power plants are still positive but decrease down to 0.1 when the distance is increasing to around 1 000–1 500 km, in a Swedish context [5]. Also in a Nordic context, it is found that the dispersion of wind power leads to a smoothing effect [15]. The smoothing effect is mainly seen from the standard deviation decreasing when comparing aggregated data from one single site, one country and the whole Nordic system. But it is also seen from the fact that the maximum total generation from dispersed wind power plants decreases with distance, while the minimum total generation increases. Further, it is observed that the correlation between wind power in Denmark and Sweden is higher than that between Denmark and Norway. This is due to the Swedish and Danish power generation sites being closer to each other since Sweden has a lot of wind power sites in the south [15].

For solar power in a future Swedish scenario, the patterns are weaker; the correlations between the power plants slightly decrease with distance, but then converge to around 0.8 [5]. This can be partly explained by the diurnal and seasonal patterns of solar irradiance, which are highly similar over a large geographical area. However, solar irradiance also has stochastic fluctuations from cloud cover, but it has a small impact on the energy output compared to the diurnal and seasonal patterns. Only the energy output affected by cloud cover can benefit from spatial dispersion [16].

Spatial correlations between solar power plants and wind power plants are less significant than those between dispersed solar power plants or dispersed wind power plants. According to the future Swedish scenario study by Widén et al. [5], spatial correlations between a solar power plant and a wind power plant are around -0.2 regardless of the distance between them.

2.4 Regional Grid Structure and Operation

As previously mentioned in Chapter 1 the distribution grid in Sweden is divided into the regional and the local grid. The regional grid connects the transmission grid to the local grid and usually maintains a voltage level between 20 and 130 kV [4].

Three types of power lines are used to distribute electrical power: overhead lines, underground cables and submarine cables [36]. In Sweden, the regional grid mainly consists of overhead lines [37]. The overhead lines are maintained regularly to reduce the risks of faults. This is done through regular tree-cutting along the path of the overhead lines. This makes the overhead line a safe, reliable and efficient technology within the regional grid [37]. The underground cables are mostly used in local distribution grids, but can also occur in regional grids [38]. The reason for not using underground cables on a larger scale in regional grids is that the technical challenges increase for power lines with greater distances and rising voltage levels. Troubleshooting and repairing underground cables can take a long time as it is difficult to see where the fault has occurred and also to dig into the ground to repair the damage [38].

There are two types of distribution systems, radial and ring main systems [39]. Low voltage distribution systems, such as the local grids and some regional grids in Sweden, are radially operated. This means that there is only one feeding point where the power comes from and is later distributed. The supply system beyond the fault gets isolated in case of failure at any

point, causing a non-continuous supply. To ensure a continuity of supply, an alternate path for the supply of power should be provided and this is possible in a ring main system, which is the system used for the high voltage distribution [39].

Power grids also consist of several components, for example, transformers, fixed shunts and switched shunts. Fixed and switched shunts are used to maintain the voltage level within bounds, reduce power losses and improve power factor [40]. A fixed shunt is connected parallel to the line or transformer, it provides a fixed amount of reactive power compensation to the power system. A switched shunt can be turned on or off by a control signal, it is used to provide reactive power based on the real-time needs of the power system [40]. A transformer is used to change voltage levels. For example, when electrical power is generated from a power plant, the voltage level has to be adapted by a transformer to the level of the grid to minimise losses during distribution [41].

2.4.1 Thermal Rating of Lines

The capacity of an overhead line is the maximum amount of current the line can withstand before it heats beyond its maximum operating temperature. The capacity is dependent on ambient conditions. Overhead lines are often designed for summer conditions since those are the worst case conditions, this is called static line rating [42]. For colder countries it is usual to have two worst case conditions to determine the capacity, one during the summer period and one during the winter period [43]. However, less severe conditions exist for the majority of the year and for these conditions, a higher capacity could be allowed [42]. Dynamic line rating (DLR) is a technique that provides information on the actual transmission capacity that is present at any given moment [42] [44]. If the information can be integrated with the system from the control room, the operation of the power system can be adapted to the prevailing conditions on individual power lines and periodically increase the capacity [44].

The highest potential for increasing the capacity is observed in areas of high wind energy, where convective cooling and loading of overhead lines are strongly coupled [42]. In Sweden there is a positive correlation between high wind power generation and weather that increases the transfer capacity of the power system [45]. This implies that the probability is low that there are favourable wind conditions and extreme heat occurring at the same time. Therefore, if DLR is implemented with wind power generation, the estimated time for overloading can be reduced significantly. However, the wind speed is often lower at the power line than at the rotor blades of the wind turbine. It is also difficult to predict the wind speed along an entire power line at windy weather conditions [45].

Countries with colder climates have a benefit concerning the temperature aspect of DLR [43] [45]. This is because high power demand often correlates with low temperatures. In Sweden, the highest load of customers is during winter when it is cold, this coincides with an increased possible line rating of the power lines if DLR is used [43] [45].

Over the past couple of decades, a number of technologies, systems and methods have been developed to enable the use of DLR [46]. Each method and system has advantages and drawbacks concerning accuracy, reliability, cost, maturity and ease of integration. The potential of DLR is big, however, there are several challenges remaining that prevent widespread implementation [46].

2.4.2 Voltage Fluctuation

There are numerous aspects to consider when determining power quality, one of which is voltage fluctuation [47]. Voltage fluctuation is the change in voltage magnitude which can be caused by, for example, short term solar irradiance variations. Overvoltage and undervoltage can damage and decrease the life span of electronic components [47]. The Swedish Energy Market Inspec-

torate [48] has a collection of regulations which deals with requirements that must be met for the transmission and distribution of electricity to be considered of good quality. Concerning voltage fluctuation, it should be kept within 90 and 110% of the nominal voltage level. This applies to both slow variations for an average of ten minutes, as well as fast variations. [48].

Jamal et al. [47] mention a number of studies that have been performed on the voltage fluctuation impacts from the integration of variable energy sources into the power system [49] [50] [51]. It is clear that voltage fluctuation is the main power quality limitation when integrating solar power into local distribution grids [47]. The fluctuations are caused by short term solar irradiance variations. One approach to minimise the impact of voltage fluctuation is, among others, geographical dispersion. By having a more even power output to the power system, through geographical dispersal of intermittent power generation, the voltage levels can be kept more constant [47].

A conventional method to reduce power fluctuations, and thus ensuring acceptable voltage levels, is by curtailing power from PV. The output power is limited by controlling the maximum power output, known as maximum power point tracking. Dump load is another conventional method. A dump load is installed to smoothen the fluctuation by absorbing excess solar power generation, resulting in power loss. Other examples of methods for reducing fluctuations are batteries, capacitors, fuel cells or diesel generators [52].

2.5 Power System Analysis

Power system analysis involves the comprehensive evaluation of a power grid model and its components from various perspectives. The main goal is generally to determine voltages at various buses and currents flowing in power lines, considering different scenarios [53]. These scenarios can include normal and faulty situations, as well as steady-state and dynamic simulations [40]. In this section, some of the aspects of power system analysis will be presented, in terms of power flow analysis and hosting capacity.

2.5.1 Power Flow Analysis

In Sweden, simulations and analyses of the transmission grid and distribution grids are performed using PSS/E [54]. PSS/E is a software tool which allows you to perform a wide variety of analysis functions to simulate and analyse electrical power transmission grids. The simulations can be performed in steady-state and dynamic conditions. PSS/E is used in over 140 countries and is one of the leading power transmission analysis and simulation tools [55]. Based on this, it is reasonable to use PSS/E to simulate and analyse the grid case in this thesis.

The power-flow problem to solve in PSS/E is the computation of voltage magnitude and phase angle at each bus in a power system under balanced three-phase steady-state conditions [40]. The starting point of solving a power-flow problem is a single-line diagram of the system. A single-line diagram is representing a power system using symbols for each component [40]. It consists of lines, buses and other components [56]. The lines carry electricity from one point to another, buses are nodes where several components like generators, transformers, and loads are connected. The buses can be categorised into load buses, generator buses or reference buses. A load bus (also known as a P-Q bus) represents the point of consumption of electricity where the active and reactive power demand is specified. A generator bus (also known as a voltage control bus or P-V bus) represents the point of generation of electricity, where the active power and voltage magnitude is specified. A reference bus (also known as slack bus or swing bus) does not exist in real-life power systems, it is used as a reference bus in power flow studies to absorb or emit the active or reactive power in order to keep the power system in balance [56]. The input data

required for the computations is obtained from this single-line diagram. This input data consists of line data, bus data and transformer data. Each bus, k , has the following variables: voltage magnitude V_k , phase angle δ_k , net active power P_k and reactive power Q_k . Two of these variables are known input data and the other two variables are to be computed by PSS/E [40].

Solving a power flow problem can be described as in the following paragraphs. In a general circuit with $N + 1$ buses, one bus is selected as the reference bus, in this example called bus 0. The voltages at the remaining buses are defined with respect to the reference bus, meaning that the bus voltages V_{10} , V_{20} , ..., V_{N0} are defined with respect to bus 0. A nodal equation system can be formulated in a matrix format as

$$\begin{bmatrix} Y_{11} & Y_{12} & Y_{13} & \dots & Y_{1N} \\ Y_{21} & Y_{22} & Y_{23} & \dots & Y_{2N} \\ Y_{31} & Y_{32} & Y_{33} & \dots & Y_{3N} \\ \vdots & \vdots & \vdots & & \vdots \\ Y_{N1} & Y_{N2} & Y_{N3} & \dots & Y_{NN} \end{bmatrix} \begin{bmatrix} V_{10} \\ V_{20} \\ V_{30} \\ \vdots \\ V_{N0} \end{bmatrix} = \begin{bmatrix} I_1 \\ I_2 \\ I_3 \\ \vdots \\ I_N \end{bmatrix}, \quad (4)$$

which can be written in matrix notation as $\mathbf{Y}\mathbf{V} = \mathbf{I}$, where \mathbf{Y} is the $N \times N$ bus admittance matrix, \mathbf{V} is the column vector of N bus voltages, and \mathbf{I} is the column vector of N bus currents [40]. All diagonal elements, Y_{kk} , and all off-diagonal elements, Y_{kn} , can be written as

$$Y_{kk} = \text{sum of admittances connected to bus } k \quad (k = 1, 2, \dots, N), \quad \text{and} \quad (5)$$

$$Y_{kn} = -(\text{sum of admittances connected between buses } k \text{ and } n) \quad (k \neq n), \quad (6)$$

respectively [40]. The equation for the k^{th} bus is written as

$$I_k = \sum_{n=1}^N Y_{kn} V_n, \quad (7)$$

derived from Equation (4). The complex power delivered to bus k is calculated according to

$$S_k = P_k + jQ_k = V_k I_k^*, \quad (8)$$

where S_k [VA] is the apparent power, P_k [W] is the active power, Q_k [VAR] is the reactive power which is the imaginary part, V_k [V] is the voltage and I_k^* [A] is the conjugate of the complex current I . The voltage and admittance terms are defined as

$$V_n = V_n e^{j\delta_n}, \quad \text{and} \quad (9)$$

$$Y_{kn} = Y_{kn} e^{j\theta_{kn}} = G_{kn} + jB_{kn}, \quad (10)$$

where δ is the voltage angle, θ is the impedance angle, G is the conductance, B is the susceptance which is the imaginary part, and $k, n = 1, 2, \dots, N$. By combining Equation (7), (8), (9) and (6), and separating the real and imaginary parts, P_k and Q_k can be written as

$$P_k = V_k \sum_{n=1}^N Y_{kn} V_n \cos(\delta_k - \delta_n - \theta_{kn}), \quad \text{and} \quad (11)$$

$$Q_k = V_k \sum_{n=1}^N Y_{kn} V_n \sin(\delta_k - \delta_n - \theta_{kn}), \quad (12)$$

for $k, n = 1, 2, \dots, N$. By setting the injected P and Q, see Equation (11) and (12), for each bus in the power system, a power flow problem is created. The power flow solutions can be retrieved with, for example, a Newton-Raphson approach as the optimisation solver. This is often performed using a software tool, such as PSS/E [40]. Generally in power system analysis, values are presented per unit. A per unit value is dimensionless and it is defined as the ratio between a value in any unit and the base or reference value in the same unit [40].

2.5.2 Hosting Capacity Methods

As mentioned in Chapter 1, one way of evaluating the possibility of accepting more renewable power sources to the power system is assessing the hosting capacity [9]. The hosting capacity is decided by different performance indices of the power system and their limits and can be increased by doing different reinforcements of the power system, or can show the acceptable limit if no further investments are done [7]. These performance indices and their limits must be specified in order to study the hosting capacity [7]. In German areas with a lot of solar power, overvoltage is a common limiting factor of hosting capacity [57]. Other less common examples of power quality factors affecting a distribution grid are flickers, harmonics and phase imbalances [57]. Even more factors that have been investigated in previous research include voltage unbalance, supraharmonics, intraharmonics, protection and losses [7]. However, the most common in recent research studies of hosting capacity is to study the voltage magnitude and thermal loading of lines and transformers [7].

The methods for assessing hosting capacity can be divided into three main groups: deterministic, probabilistic and time series [7]. The different types of methods come with different strengths and shortfalls and are possible for different applications and procedures. Therefore, the prerequisites on accuracy but also the data, time and computational power available must be assessed before choosing a suitable method [7]. When it comes to accuracy, it is important to remember that there exists no such thing as a strictly "safe" hosting capacity as it is impossible to cover all possible scenarios; the only way to assess such would be to accept infinite investments in the power system [58].

The deterministic methods are based on using fixed data, known single point input values of load and power generation, when evaluating the power system. Regarding intermittent power generation, this would mean the maximum capacity as the power generation value [7]. This is the traditional approach and the base calculation for hosting capacity [8], but it uses a worst case scenario which could lead to an underestimation of the hosting capacity [6]. These methods can therefore be considered conservative. The output is also a single fixed value and not a range which might be more realistic [7]. Usually, only a few scenarios representing variations of worst cases are evaluated, which makes the procedure rather fast and simple [7]. The usage of few scenarios requires some skills from the analyst as it is of utmost importance that the scenarios being evaluated are the most critical and important to cover. In a power system with growing uncertainties, it can be precarious to use only deterministic methods as it is difficult to find the most critical scenarios to evaluate [8]. The deterministic methods do not include the probability of these scenarios actually occurring and they also do not incorporate any relations between the input values, such as correlations [58].

The probabilistic methods, or stochastic methods, apply probability distribution functions (PDFs) on the input values, and thus also on the outputs. Therefore, they consider uncertainties more than deterministic methods. For example, the uncertainties of weather circumstances

for wind or solar power can be taken into consideration using a PDF, which is considered an improvement [7]. Probabilistic methods can be divided into two main types, where one relies on combined probability functions of for example all generation in the system, and the other relies on Monte Carlo Simulations. Monte Carlo simulations can represent an entire system by choosing many random scenarios to simulate [58]. The probabilistic methods can become very complex and the result can require further interpretation, which might be precarious. It can also require a lot of computational power [7]. However, they are strongly recommended by for example the European Commission [58], which claims that the probabilistic methods have undeniable advantages over deterministic ones when it comes to assessing the general adequacy of a power system. The European Commission further claim that Monte Carlo simulations are the only suitable probabilistic method to represent all aspects of a power system. Also, Ismael et al. [59] and CIGRE [8] claim that a probabilistic way of looking at hosting capacity, considering uncertainties, is to prefer over a deterministic.

The time series methods use time series for power generation and load as input values, either modeled or historical data [7]. This results in time series outputs, of which conclusions can be drawn, usually based on the worst occasions in the time series. These methods take into account the natural variation in power generation and load over time and the temporal correlations between different parameters in the power system. However, they do not take into account the probability of changes in the future, as historical or modeled data is used. They also require a lot of data and might become computationally expensive [7].

Table 2 presents an overview of the three groups of hosting capacity methods, together with advantages and drawbacks.

Table 2: A summary of the deterministic, probabilistic, and time series methods used to estimate the hosting capacity.

	Deterministic methods	Probabilistic methods	Time series methods
Input	Single value (worst case)	PDFs	Time series
Output	Single value (worst case)	PDFs	Time series
Advantages	Fast, simple, conservative	Consider uncertainties and probabilities	Consider temporal correlations and variations
Drawbacks	Single value output instead of the more realistic range output, difficult finding worst cases	Complex, require interpretation, computationally expensive	Require much data, computationally expensive

Other methods can be used for power system analyses, for example, Artificial Intelligence (AI). Shah et al. [60] conclude in their paper that AI techniques are being used when conventional methods fail to provide accurate results. The AI techniques are useful in planning, controlling, and forecasting activities in a power system. However, there is still more research needed to fully utilise the potential of AI technology in power system analyses [60].

3 Method

In the following sections the overall method is presented. It involves modeling solar and wind power, installing a combination of these and assessing the hosting capacity of the grid using two different methods. The modeled power data is also used to present a map of the correlations between solar and wind power in the area. The two different hosting capacity methods are compared and evaluated in terms of assessed hosting capacity and risk. The assessed hosting capacities are set in relation to the complementarity illustrated in the correlation map.

The overall method is visualised in Figure 2. To perform the power system analyses, ten different buses of the power grid case are randomly selected to where the new power generation is installed. The choice of ten buses is considered to be sufficient for illustrating the possible differences in results from connecting power generation to different parts of the power system, without becoming too computationally expensive. For the correlation map, a 4×4 km² grid of locations is examined based on the literature of Montforti et al. [61], Holttinen et al. [15], Sun et al. [10], and Widén et al. [62]. Solar irradiance, temperature and wind speed data are retrieved in order to model power generation for all buses and locations. Wind speed data is processed for the used wind turbine hub height, and the modeled wind power is then validated against existing historical data from Ellevio. The solar and wind power data are also validated in terms of capacity factors which are compared to the capacity factors mentioned in Section 2.1 and 2.2. Using the modeled power data, the correlation map can be created and the power system analyses can be performed with the two different hosting capacity methods. Modeled power data is only used for the new power generation in the time series method since the deterministic method is based on a constant value of power generation representing the maximum capacity. Finally, the methods are compared in regard to result and risk, and the results are connected to the correlation map. The different steps in Figure 2, along with assumptions and justifications, are described more thoroughly in the following sections of this chapter.

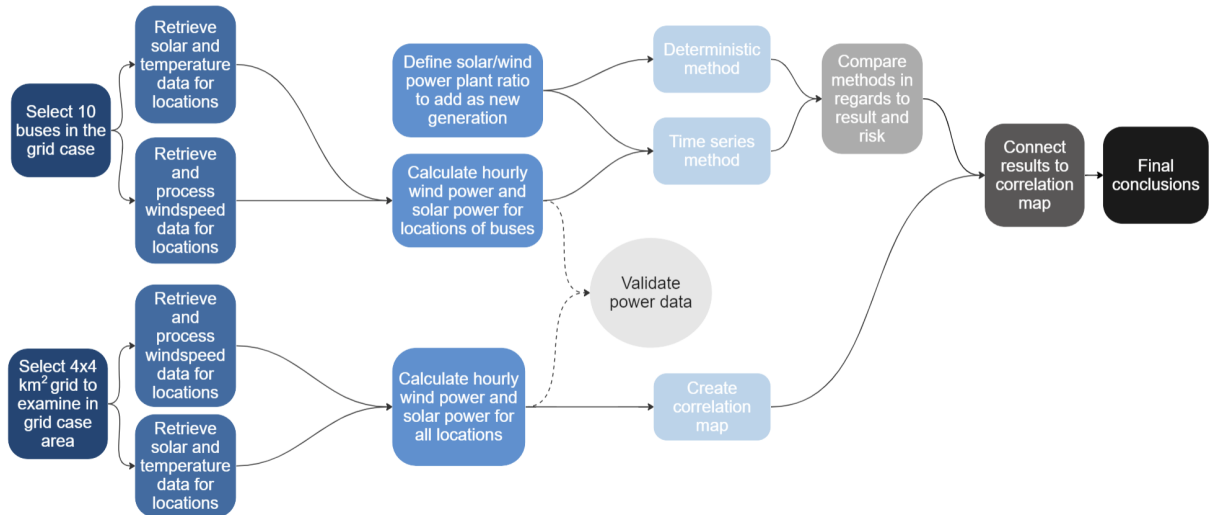


Figure 2: A flow chart of the overall method.

3.1 Renewable Power Generation Modeling

In this section the method for modeling generation from solar and wind power plants is described. This includes weather data processing, modeling of solar and wind power, and creation of a correlation map.

3.1.1 Weather Data Processing

The required weather data for modeling solar and wind power correlation is gathered for a number of locations from the data analysis tools Visual Crossing [63] and SMHI STRÅNG [64]. From Visual Crossing, wind speed data and temperature data are retrieved. From SMHI STRÅNG, global irradiance, direct normal irradiance and diffuse irradiance are retrieved.

The wind speed data gathered is measured at the height of 10 m [63], and while this is useful for the modeling of solar power generation, it is not adequate for the modeling of wind power generation as wind turbines have a higher height. Wind speed at 100 m is available at Visual Crossing, but not for the year 2020, which is the year that the studied grid case is based on. Therefore, the wind speed at 10 m has to be extrapolated to the height of 100 m, in order to model the wind power generation. As described in Subsection 2.1.1, wind speed at different heights can be calculated in different ways which all brings uncertainties. In this thesis, the power law equation is used since it is the most common approach when insufficient information is available. Initially, the power law exponent is set to the value of $\alpha = 1/7 = 0.14$ which is a value recommended if topology information is unavailable [27]. The wind speed at 100 m, estimated using the power law, is then compared with wind speed data at 100 m from Visual Crossings to ensure accuracy. The year 2022 is used, for which data from Visual Crossing exists. The comparison shows that the Visual Crossing wind speed is higher than the extrapolated wind speed, meaning that Visual Crossing uses a different mathematical approach or different power law exponent. To get more accurate wind speed data at 100 m, the power law exponent is changed. The new power law exponent is calculated by using an optimisation solver in Excel for a number of equally distributed locations in the area. For each location, an optimal power law exponent is calculated, where optimum is defined as the power law exponent that minimises the sum of the squares of the differences between Visual Crossing's wind speed data at 100 m and the calculated data. This results in a number of different power law exponents and the average of these is used. The final value of the power law exponent is $\alpha = 0.31$, and is then used for extrapolating the wind speed from 10 m to 100 m for the year 2020.

3.1.2 Wind Power Modeling

Wind speed data is used as input values to model a wind turbine in Python. The wind turbine used is called Vestas V164-8.0 which is a three-bladed turbine, see Table 3 for the turbine data [65]. The choice of the wind turbine is based on the largest wind turbines with available wind power curve data. Among these, Vestas V164-8.0 is chosen since Vestas is one of the largest wind turbine manufacturers and is a global leader in installing wind power [66]. The turbine data is used in a Python script to generate a power curve of the wind turbine, from which a function of how the power varies with different wind speeds is achieved.

Table 3: Wind turbine data for Vestas V164-8.0 [65].

Parameter	
Rated power	8 MW
Cut-in wind speed	4 m/s
Rated wind speed	13 m/s
Cut-out wind speed	25 m/s
Hub height	100 m

Wind speed data, extrapolated to the turbine hub height of 100 m as described in Subsection 3.1.1, is used with the power curve function for each hour of the year. The outcome is power generated by the wind turbine during the year 2020. To validate the method and the modeled wind power data, the same calculations are done on locations where Ellevio have wind power plants installed with available historical wind power data. In Figure 3 the modeled and historical data are presented for each month for one of the locations where a wind power plant of 60.8 MW installed capacity is located. Comparing the modeled data with the historical data, it is clear that the modeled data follow the same trend as the historical data and the values of the modeled data are close to the historical values. Thus, the method for modeling wind power is considered reasonably accurate.

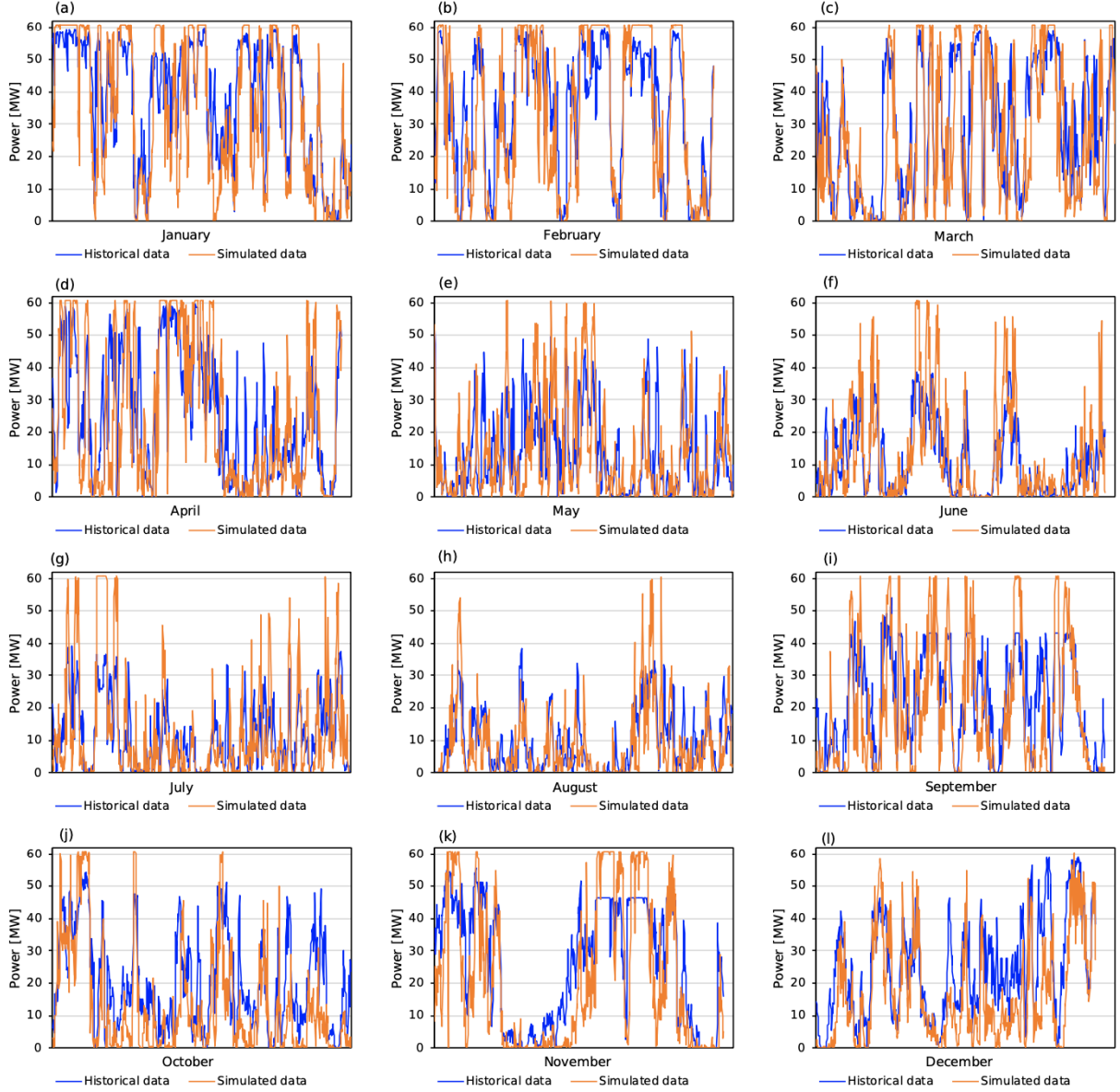


Figure 3: A comparison of modeled and historical data for a location with an existing wind power turbine of 60.8 MW installed capacity. Figures (a) to (l) represent the months of January to December.

3.1.3 Solar Power Modeling

Solar irradiance data and other weather data are used to model solar power in Python, using a Python class called ModelChain from the package pvlib, provided by Holmgren et al. [67]. This Python package has been used before in for example the work of Liu et al. [68] and Lohr et al. [69]. ModelChain uses weather data and location as inputs to calculate the solar power output. Required weather data are global irradiance, direct normal irradiance, diffuse irradiance, temperature and wind speed. ModelChain includes several databases of needed information on PV modules and inverters, of which the databases from California Energy Commission (CEC) [70] are used. The used PV module for the modeling is a Sunpower X22 370 adapted for commercial purposes, with a maximum power of 370 W DC, and the used inverter is a Fronius Primo 15.0-208-240. The module is chosen based on its high efficiency [71], as well as its availability in pvlib. It is important to choose components with high efficiency in the modeled PV system. If the efficiencies are underestimated, it can lead to an overestimation of the power grid's hosting

capacity. This is because the modeled solar power could then be lower than the actual solar power generation, which could make the assessed hosting capacity higher than what the power grid can handle. The inverter is also chosen based on its availability and it is also considered efficient with its 97% efficiency, however, it requires some power also during times with no solar irradiance, meaning that the overall output will be negative during nighttime [70].

The PV system is configured with 13 modules mounted on each string, with four strings on each inverter. This configuration gives generation levels within ranges for the inverter in terms of voltage and current. It also gives a DC/AC ratio of around 1.283, which is close to 1.3, described as an optimal and common value in Section 2.2. The variation of the module temperatures is estimated based on open rack modules, as a commercial power plant is assumed. No losses from the angle of incidence aspects or from different wavelength spectrums are considered, in order to simplify the model and reduce the need for data. As mentioned in Section 2.2 the angle of incidence and the spectral effects show a smaller impact on the efficiency compared to the temperature of the module, which justifies neglecting those parameters in the pvlib package. Also, if these losses were taken into consideration, the modeled PV system would get a lower overall efficiency. As previously mentioned, it is important to have components of high efficiency in the modeled PV system to not risk overestimating the hosting capacity. To further model efficient modules, the angle and direction of the modules are chosen to generate as much power as possible, which in Sweden corresponds to an angle of 40 degrees and a southern direction [72] [73].

3.1.4 Correlation Map

Temporal correlations between solar and wind power are calculated over an area approximately corresponding to the studied regional grid case. When calculating wind and solar correlations, the wind and solar data needs to be of the same unit. Hence wind and solar weather data are used to model solar and wind power data as described in Subsection 3.1.2 and 3.1.3 respectively, and then normalised. Temporal correlation is chosen since it is seen as most relevant based on the purpose of the correlation map; as the solar and wind power generation is modeled as co-located, any spatial correlation is out of interest. Thus, the correlation map shows how solar and wind power correlate in each location but it does not show how solar and wind power correlate in relation to another location. The correlations are calculated with the Pearson correlation coefficient described in Section 2.3.

The scale or grid size of the meteorological data and the correlation map needs to be comprehensive enough but not take significant computational time. Montforti et al. [61] and Holttinen et al. [15] used a grid size of $4 \times 4 \text{ km}^2$ while for Sun et al. [10], the equivalent value was $3 \times 3 \text{ km}^2$ for wind power and $4 \times 4 \text{ km}^2$ for solar power. Widén et al. [62] argue that for solar irradiance, a "dense grid" is needed to capture variations over a smaller temporal and spatial scale, and gives an example of $4 \times 4 \text{ km}^2$ of such. Based on these works, a distance of 4 km from each location is used in this thesis, which represents 1 279 locations.

3.2 Studied Grid Case

The grid case used in this thesis is provided by Ellevio and consists of 49 buses. The grid is anonymised and simplified by Ellevio but should represent a realistic actual part of the regional grid in the middle of Sweden. The area of the power grid is approximately $160 \times 110 \text{ km}^2$ and the nominal voltage level of the grid is 140 kV. A single-line diagram representing the grid is seen in Figure 4. The two blue buses in the figure represent the reference buses to which the remaining green buses are defined in respect to. The two reference buses represent the transmission grid. See

Section 2.4 and Subsection 2.5.1 for explanations of the remaining components in the single-line diagram.

It has been shown by Sun et al. [10] and Ismael et al. [59] that the hosting capacity can vary widely depending on where in the power system the generation is connected. Therefore, for the different methods, the new power generation will be added to the same buses. The methods are also iterated for ten different, randomly chosen buses. It is assumed that ten buses, which correspond to around 20% of all buses, should be enough to illustrate the possible differences in results from connecting to different parts of the power system. The modeled power generation is added to the buses marked as A to J in Figure 4.

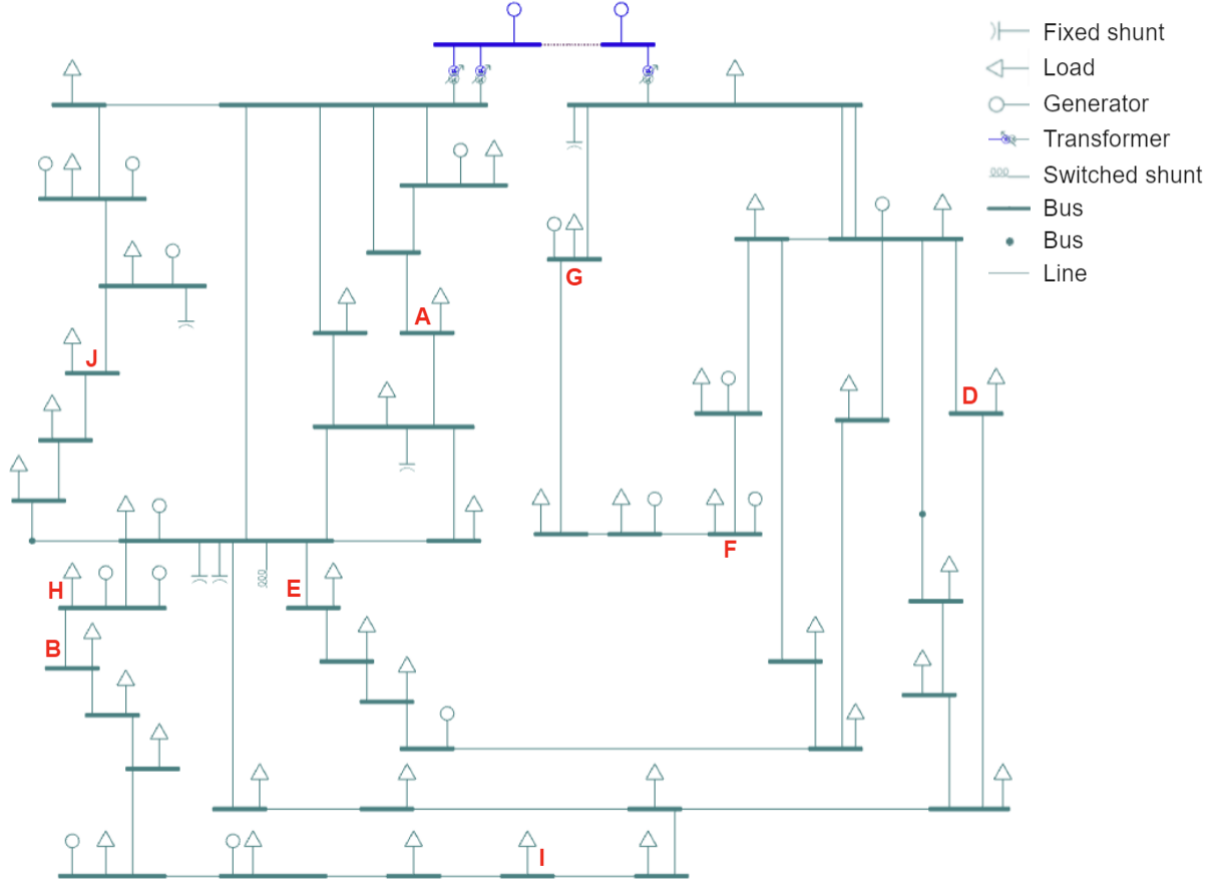


Figure 4: The anonymised and simplified grid case with the ten randomly chosen buses marked with A to J.

New power generation is modeled as described in Section 3.1. The new power generation is assumed to consist of 70% wind power and 30% solar power in all cases. This ratio is chosen based on the conclusions from the Swedish future scenario studied by Widén et al. [5], where a 3-to-7-ratio seem to have the most even capacity over the year, measured on a national scale where this ratio showed the lowest standard deviation.

Historical hourly data of power generation and load connected to the buses in the grid is given for the year 2020. The studied year of 2020 is a leap year of 8 784 hours. However, some of the buses lack historical data for the last 48 hours of this year, these 48 hours are therefore neglected for all data so that the studied year consists of 8 736 hours. The power generation in the grid mainly consists of wind and hydro power plants. No large-scale solar power plants are directly connected to the grid, however, there might be smaller solar power plants connected to the local grid on lower voltage levels. These solar power plants are included in this grid case in combination with loads. The maximum capacity of the power generation varies from 1 to 170 MW. Some of

the buses lack historical power generation data for the year 2020 since the power plants of these buses were installed after 2020. Power generation from these buses should still be considered in the power flow analyses of the grid case since they are planned to generate electrical power in the future. At Ellevio, confirmed future power plants are taken into consideration when evaluating if new power generation can be installed. Therefore, power generation for these buses is modeled as described in Section 3.1, with known wind turbine capacities.

The hosting capacity for each method is retrieved based on how much modeled power can be connected to the grid case without unacceptable limits being reached. These limits are below 0.9 or above 1.1 of voltage level per unit, or above 100% of line loading for the deterministic method. For the time series method, the line loading can be exceeded for a shorter period of time. In this specific grid case, the accepted line loading is around 125% during winter hours and 160% during summer hours. The line loading is dependent on the capacity of the line, also known as the line rating. The line rating is different depending on season, due to the temperature effects on line ratings described in Subsection 2.4.1. At Ellevio, summer's line ratings are used from the 1st of May to the 31st of September, and therefore they are used for the same time period in this thesis. The summer's line ratings are approximately 63% of the winter's line ratings in the given case.

3.3 Hosting Capacity Methods

Two different hosting capacity methods are tested on a grid case with power flow analyses, using the software PSS/E. All iterations of the PSS/E simulations are automated with Python scripts that change input parameters and run analyses. The limiting factors considered for assessing the hosting capacity are voltage variations and overloading of lines. These are chosen as they are the most common to investigate [7] and also straightforward to evaluate in PSS/E. A deterministic method and a time series method are considered suitable to compare as the deterministic method does not take into account the complementarity while the time series method does. They are also both straightforward and common. A probabilistic method is not taken into consideration as it is more complex and requires a lot of resources in regard to data, computational time, and also knowledge for interpreting the results. The two chosen methods are here further described.

3.3.1 Deterministic Method

A deterministic method for assessing hosting capacity is generally based on historical power generation and load data and uses single values as inputs and outputs as described in Subsection 2.5.2. The input data represents a worst case scenario where the grid case shows a low load and a high power generation. To find this worst hour, the net power output was used, see Figure 5. The net power output is calculated by subtracting load from power generation in the studied grid, meaning that the positive values in the figure are net power generation exported to the TSO and the negative values are net load. The worst hour for connecting new generation is assumed to be the hour which has the highest net power output in the grid. This assumption is valid in the absence of knowledge about local limitations in the grid. In the power grid case, no large-scale solar power generation is connected, the main generation sources are therefore wind power and hydro power. Wind power [74] and hydro power [75] generally produce more during the winter months. The worst hour during the year is therefore not unexpectedly found in the winter, 23rd of February 03:00, see the marking "Worst Case Winter" in Figure 5.

However, in a power system with large-scale solar power connected, as simulated in this thesis, also the summer months might be crucial. It is therefore decided to choose a similar hour during the summer. This worst case hour is also used to estimate the hosting capacity, and the lowest

hosting capacity between Worst Case Winter and Worst Case Summer is the hosting capacity of the deterministic method. The Worst Case Summer is important to study for several reasons besides that solar power usually has a higher generation during summer. Wind power can also have high generation as seen in 3.1.2 Figure 3, and the load in Sweden is lower. Also, the lines have lower ratings during summer than winter, around 63% of the winter ratings, as mentioned in Section 3.2. These circumstances might limit the hosting capacity differently during the summer compared to the winter.

To retrieve this Worst Case Summer, the months May to August are analysed as they had the most solar power generation in SE3 during 2022 [76]. Only the hours in the middle of the day, 11:00-15:00 with daylight saving time, are extracted as they are assumed to be critical when solar power generation is added to the power system. The hour with the highest net power generation that fulfils these criteria is the 16th of May 12:00, see the marking "Worst Case Summer" in Figure 5. Note that this hour is not the highest peak during May to August, there are hours where the net power output is higher but those hours do not occur during 11:00-15:00 and are therefore not chosen as the hour for Worst Case Summer.

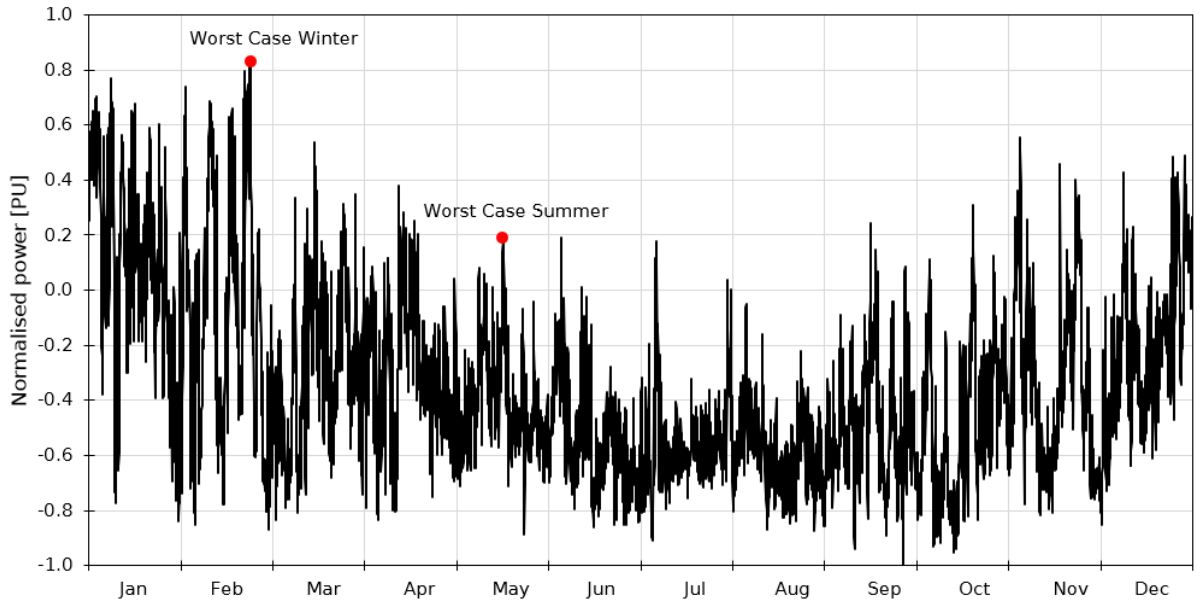


Figure 5: Normalised net power output of the power grid case during the studied year 2020. Worst Case Winter is marked on the 23rd of February at 03:00 and Worst Case Summer is marked on the 16th of May at 12:00.

The load and power generation data for these two worst hours are used as input values in PSS/E. The new power generation is then assumed to be at installed capacity when added to the power system model, meaning that both solar and wind power plants generate maximum power. A power flow analysis for this scenario is then performed in PSS/E and evaluated. The output is single point values that show if, and in that case where, overloading of lines is occurring in the power grid, as well as voltage levels outside the permitted range of 0.9 and 1.1 per unit of the nominal voltage level. If these limits are not reached, the capacity of the new power generation is scaled up with 11.435 MW and the power flow analysis is repeated. The choice of 11.435 MW is based on the 3-to-7 ratio mentioned in Section 3.2 and the wind turbine having a rated power of 8 MW. The solar power plant is therefore scaled to 3.435 MW, resulting in a scale-up step of approximately 11 MW. A smaller step than 11 MW can be chosen to increase the data resolution which might result in a more correct estimation of the hosting capacity. However, a higher data resolution requires more computational time which is not available for this thesis. The scale-up is iterated until overloading or voltage limits are reached, and then the process starts over again

for the next of the ten buses in the power grid case. When the process is finished, the results are evaluated and the hosting capacities of the two worst case hours are retrieved. The final hosting capacity of the deterministic method is based on the lowest hosting capacity for each bus when comparing Worst Case Winter and Worst Case Summer. The process of the deterministic method is presented as a flow chart in Figure 6.

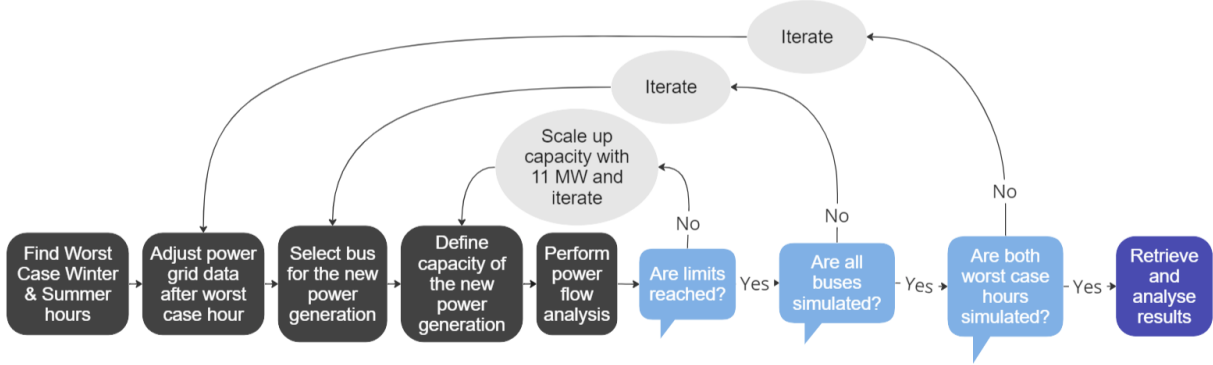


Figure 6: A flow chart of the deterministic method.

To illustrate the outcome of this method, a fictional example of the loading of lines is further presented in the following paragraphs. This example has four buses (1, 2, 3 and 4) which are connected with lines in between them (1–2, 2–3 and 3–4), see Figure 7. In Figure 7 (a) no new power generation is installed. The new power generation is then installed in Bus 1 and the capacity is increased until overloading occurs. As seen in Figure 7 (b), overloading occurs in Line 2–3.

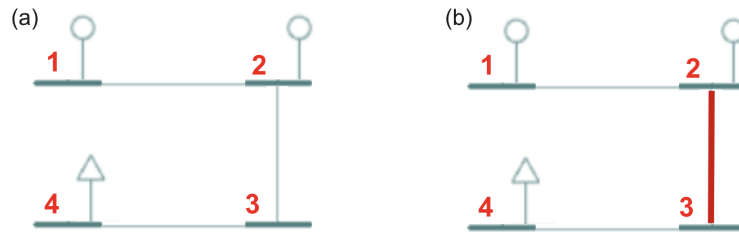


Figure 7: A fictional example of a part of a power grid consisting of four buses (1, 2, 3 and 4) and three lines (1–2, 2–3, 3–4). No new power generation is installed in (a). In (b) new power generation is installed in Bus 1 and the capacity is increased until Line 2–3 overloads.

The simulations are performed and the results are gathered as the maximum loading of all lines in the power grid, these are presented in the column to the far right in Table 4. The assessed hosting capacity is determined by the highest installed capacity before reaching overloading in any line. As can be seen in red text, Line 2–3 overloads to 103% when the installed capacity reaches around 320 MW. This means that the deterministic method assesses a hosting capacity of approximately 309 MW, which is the last step of increased installed capacity without loading any lines to more than 100%. Note that overloading could occur anywhere between 309 MW and 320 MW, but the last step showing no overloading is the assessed hosting capacity.

Table 4: A fictional example of the loading of lines when power generation is installed in Bus 1. In the far right column, the highest loading of all the lines in the power grid is presented. The loading of Line 2–3 is exceeding 100% when the installed capacity is increased to 320 MW, this is marked in red. This determines the assessed hosting capacity of this method to be 309 MW.

Installed capacity [MW]	Loading [%]			
	Line 1–2	Line 2–3	Line 3–4	Maximum
11	93	91	90	93
...
309	93	95	97	97
320	95	103	99	103

The voltages of the buses in the power grid are analysed in the same way, but instead of gathering the maximum voltage level, the most critical voltage levels are gathered which corresponds to the voltage levels closest to either 0.9 or 1.1 per unit. The limit that is violated first decides the hosting capacity; either voltage levels or loading of lines. The method is iterated for the two different worst case hours and it is the scenario giving the smallest hosting capacity that determines the assessed hosting capacity. The method is also iterated for all ten buses.

Risk Assessment of Increased Installed Capacity

One way to consider complementarity between renewable power sources in a deterministic method could be to assess the risks with increasing installed capacity above the assessed hosting capacity. Consider the previous example where the retrieved hosting capacity is approximately 309 MW. When assessing the risks, the installed capacity is increased with 11 MW to approximately 320 MW. The wind and solar power generation is modeled for each hour of the year as described in Subsection 3.1.2 and 3.1.3 based on a capacity of 320 MW. The data is sorted in Figure 8, and it can be seen that for the majority of the hours, the power generation is below 320 MW. It is therefore interesting to investigate the risks that come with increasing the installed capacity above the assessed hosting capacity.

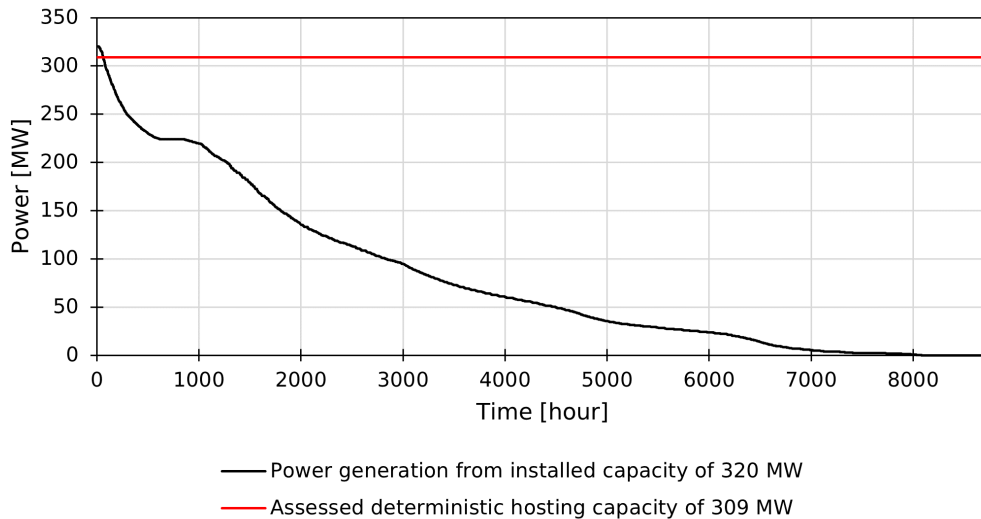


Figure 8: Power generation from solar and wind in Bus A with an installed capacity of 320 MW, sorted from lowest to the highest power, during the studied year. The red line represents the assessed hosting capacity from the deterministic method of 309 MW.

From this simulation, the number of hours when power generation exceeds the assessed hosting capacity, called overgenerating hours, can be retrieved. The risk is then calculated as the percentage of overgenerating hours of all 8 736 hours during the studied year. This risk

assessment does not say anything about how the loading of lines or voltage levels of buses are affected during the year.

3.3.2 Time Series Method

The time series method is based on historical and modeled power and load data in the form of time series. The new power generation is modeled as described in Section 3.1. Both historical and modeled data are added hour by hour to the power system, and a power flow analysis is performed for each hour during the year. The historical data consists of loads, hydro power and wind power from already existing wind power plants in the power grid. The modeled data consists of the new solar and wind power generation added to the ten different buses in the power grid. As mentioned before, the last 48 hours of the year are not considered, so 8 736 hours of the year 2020 are analysed.

In difference from the deterministic method, the time series method gives an opportunity to accept more hours of overloading without necessarily having a higher degree of overload, which the DSOs can possibly handle and it is therefore interesting to investigate. In order to present a risk-based estimate, the simulations of the hosting capacity are continued as long as less than 13 hours of overloading are reported. The choice of 13 hours is based on an assumption that the net load, and hence line loadings and voltages, is normally distributed. This means that it is assumed that all values are equally distributed above and below their mean value [77]. Then the number of hours exceeding 3σ is estimated. This corresponds to three standard deviations of the Gaussian distribution, also known as normal distribution. Using this approach 0.15% [77], or 13 hours a year, has a net load exceeding 3σ . When less than 13 hours during the year show overloading or voltage violation, the installed capacity is increased by 11 MW and the year is simulated once again, hour by hour. The assessed hosting capacity is achieved at the highest installed capacity which results in overloading or voltage violations during less than 13 hours of the year. The method is repeated for ten buses. The process of the time series method is presented as a flow chart in Figure 9.

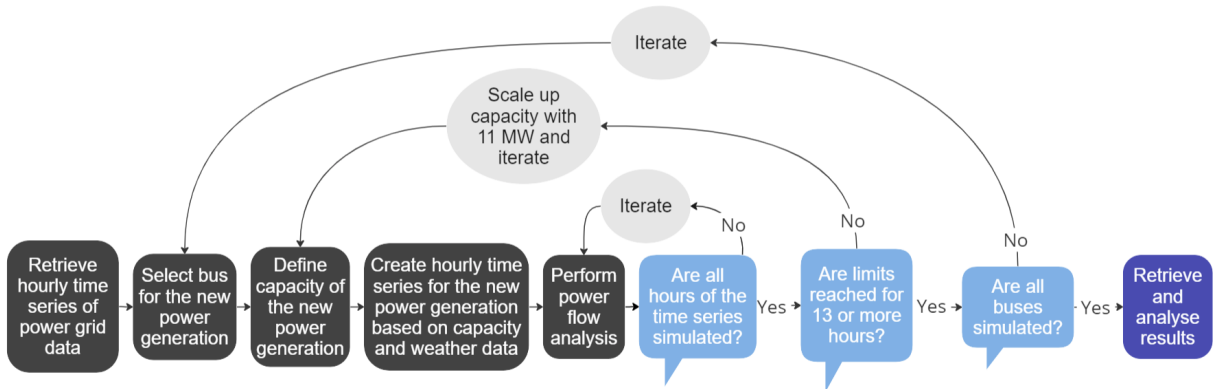


Figure 9: A flow chart of the time series method.

Table 5 illustrates a fictional example of the results from this method when installing power in Bus A. When all simulations are performed, the highest loading of lines in the power grid is retrieved and presented for each installed capacity and hour during the year. When increasing the installed power to 343 MW, the number of hours outside the loading and voltage limits exceeds 13, this is marked in red. The assessed hosting capacity is the highest installed power before exceeding the 13 hours limit, which in this example corresponds to 332 MW.

Table 5: A fictional example illustrating the maximum loading of all lines for each hour during a year. The hosting capacity is based on the number of hours with overloading per year, for different installed capacities. The number of overloading hours exceeds 13 for 343 MW, marked in red. This determines the assessed hosting capacity of this method to be 332 MW.

Hour	Max. loading [%] with an installed capacity of 11 MW	...	Max. loading [%] with an installed capacity of 332 MW	Max. loading [%] with an installed capacity of 343 MW
1	34	...	40	53
...
8 735	43	...	45	53
8 736	42	...	45	52
No. hours outside limits	0	...	9	14

4 Results & Analyses

In the following sections, the results from the deterministic method and the time series method are presented along with their assessed risks. The correlation map of solar and wind power is also presented.

4.1 Deterministic Method

In this section, the loading and voltage levels from the two worst cases in the deterministic method are presented in graphs. The assessed hosting capacities for Bus A to J for the two worst cases are presented in tables. Lastly, the two tables are combined into one table to retrieve the final results of the assessed hosting capacity for the deterministic method.

4.1.1 Worst Case Winter

Starting with Worst Case Winter, the maximum loading of all lines in the grid is presented for different levels of installed capacity at Bus A to J in Figure 10. The red line represents the limit of 100%, and the minor ticks on the x-axis represent each increased step of 11 MW installed capacity. It can be seen that Bus J has the lowest assessed hosting capacity of 80 MW before exceeding the loading limit. Bus A assesses the highest hosting capacity, with 423 MW before exceeding the loading limit. The maximum loading of lines for all buses, except for Bus J, is first decreasing linearly to later increase linearly at some point, this turning point is further on referred to as an "elbow". One possible reason for the initial decrease of loading could be that a local load absorbs the added power generation which improves the situation by lowering the loading of lines. Then at a certain point, the power generation becomes too large for the load to absorb it, causing the loading of lines to increase. Moderately increased power generation can cause improvement in the power grid in terms of loading of lines [78].

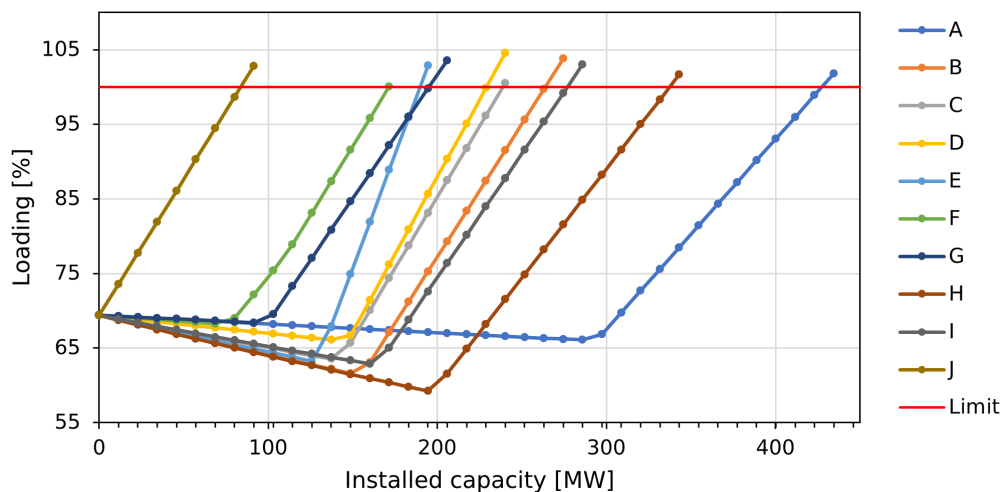


Figure 10: Maximum loading of all lines in the power grid for Worst Case Winter is presented as a function of the installed capacity at Bus A to J, increasing with a step of 11 MW. The red line represents the loading limit of 100%.

When evaluating the results closer it is established that the elbows are caused by the fact

that the maximum loading in the power grid shifts from one overhead power line to another. The maximum loading before the elbow point occurs at the same power line in the grid regardless of which bus the power generation is installed to. This power line is further called "Line X-Y". The loading of Line X-Y is then, at the elbow point, replaced by another power line which now has the highest loading in the power grid. This other line is a line connected to, or close to, the bus where the power generation is installed. In order to illustrate this elbow effect two installed capacities at Bus A are presented in Figure 11. The installed capacity in Bus A in Figure 11 (a) is 286 MW, and the line with maximum loading in the grid (Line X-Y) is shown as yellow. The installed capacity in Bus A in Figure 11 (b) is 435 MW, and the line with maximum loading in the grid is shown as red since overloading occurs. The line with maximum loading is shifted once from Line X-Y in Figure 11 (a), which explains the elbow, and it moves towards Bus A in Figure 11 (b) when the installed capacity is increased.

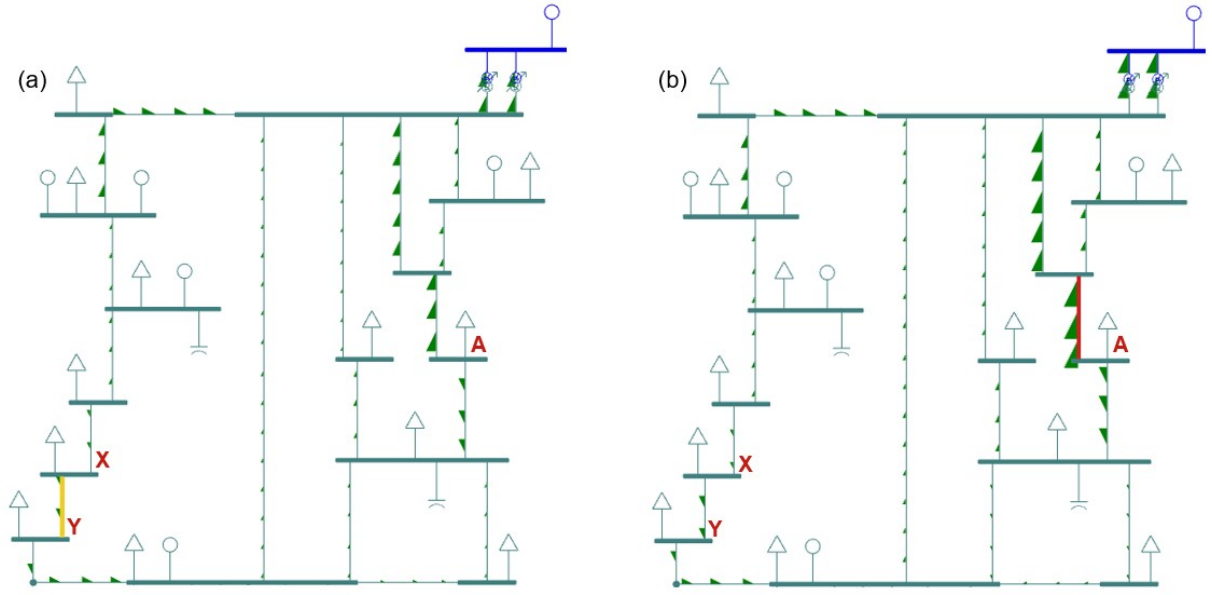


Figure 11: A part of the grid around Bus A showing the effects on the power system for Worst Case Winter when increasing power generation in Bus A. The installed capacity is 286 MW for (a) and 435 MW for (b). The arrows show the direction of power flow in the line, and they are scaled according to the amount of power. The yellow line indicates the line with maximum loading in the grid, and the red line indicates overloading.

The reason for Bus J not having an elbow is since Line X-Y is very close to Bus J, and thus the loading keeps increasing instead of shifting to a different line as the installed capacity at Bus J increases.

In Figure 12, the most critical voltage level in the grid for different levels of installed capacity at Bus A to J is presented. As mentioned in Subsection 3.3.1, the most critical voltage level is referring to the voltage level being closest to either 0.9 or 1.1 per unit. The red lines represent the voltage limits of 0.9 and 1.1 per unit. As can be seen, the voltages never reach the limits, the limiting factor is instead the loading shown in Figure 10. From Figure 12, it is clear that the voltage level is neither affected by the increase of installed capacity, nor where the power generation is installed. The bus with the most critical voltage in the power grid has a voltage of around 1.04 per unit. This is the case for all levels of installed capacity, regardless of which bus the power generation is connected to.

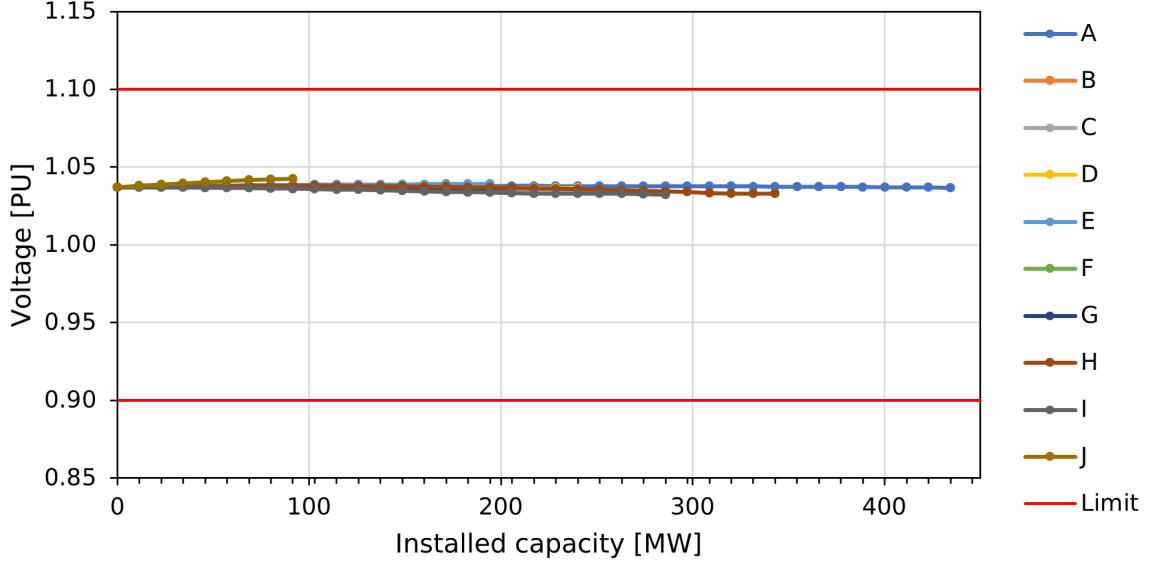


Figure 12: Most critical voltage of all buses in the power grid for Worst Case Winter is presented as a function of the installed capacity at Bus A to J, increasing with a step of 11 MW. The most critical voltage level is referring to the bus in the power grid with a voltage level closest to either 0.9 or 1.1. The red lines represent the voltage limits of 0.9 and 1.1 per unit.

Table 6 presents the assessed hosting capacity for Bus A to J of Worst Case Winter. All assessed hosting capacities are retrieved from Figure 10 since the loading of lines is the limiting factor. Bus A has the highest assessed hosting capacity, while Bus J has the lowest.

Table 6: Assessed hosting capacities for Bus A to J according to Worst Case Winter. The numbers are rounded off.

Bus	Assessed hosting capacity [MW]
A	423
B	263
C	229
D	229
E	183
F	160
G	194
H	332
I	274
J	80

4.1.2 Worst Case Summer

The maximum loading of all lines for Worst Case Summer is presented in Figure 13. Just as in Figure 10 in Subsection 4.1.1, the red line represents the limit of 100% and the minor ticks on the x-axis represent each increased step of 11 MW. It can be seen that Bus F has the lowest assessed hosting capacity of 103 MW before exceeding the loading limit. The bus with the highest assessed hosting capacity is Bus A, just as in Worst Case Winter, with 309 MW. The maximum loading of lines for all buses, except for Bus F and G, is first decreasing linearly to

later increasing at the elbow point. This is similar behaviour to what was shown in Worst Case Winter. The reason for this initial decrease is, as stated in Subsection 4.1.1, probably due to a local load absorbing the added power generation.

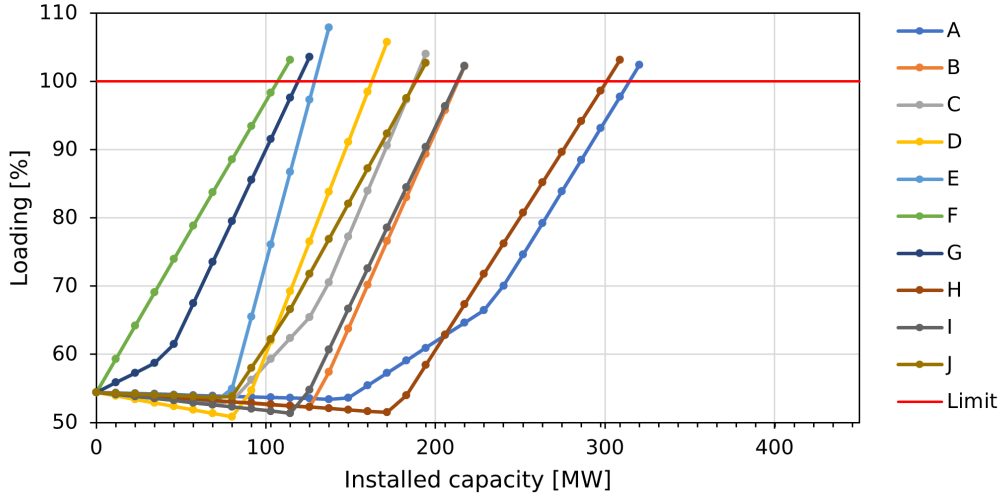


Figure 13: Maximum loading of all lines in the power grid for Worst Case Summer is presented as a function of the installed capacity at Bus A to J, increasing with a step of 11 MW. The red line represents the loading limit of 100%.

The results in Figure 13 are further evaluated to establish that the elbows are caused by the fact that the maximum loading in the power grid shifts from one line to another, just as for Worst Case Winter. The maximum loading before the elbow point occurs at the same line in the grid regardless of which bus the power generation is installed to. This line is connected to Bus F and further on called Line F–Z. This is the reason for Bus F not having any elbow, similar to how Bus J behaved for Worst Case Winter. One difference shown in this Worst Case Summer compared to Worst Case Winter is that Bus G has increased loading of Line F–Z instead of decreased loading as the rest of the buses. The reason for this could be that there is no local load close to Bus G of this worst case hour, in combination with Bus G being located close to Line F–Z which might cause the loading of Line F–Z to increase when power generation is installed in Bus G.

Just as for Worst Case Winter, Bus A and a part of the surrounding grid are presented in Figure 14 to illustrate the effects on the grid when installed capacity is increased. The installed capacity in Bus A in Figure 14 (a) and (b) is 137 MW and 229 MW respectively, and the line with the maximum loading in the grid is shown as yellow. The installed capacity in Bus A in Figure 14 (c) is 320 MW and the line with the maximum loading in the grid is shown as red since overloading occurs. The line with maximum loading is shifted two times, which explains the two elbows in Figure 13 for installed capacity in Bus A.

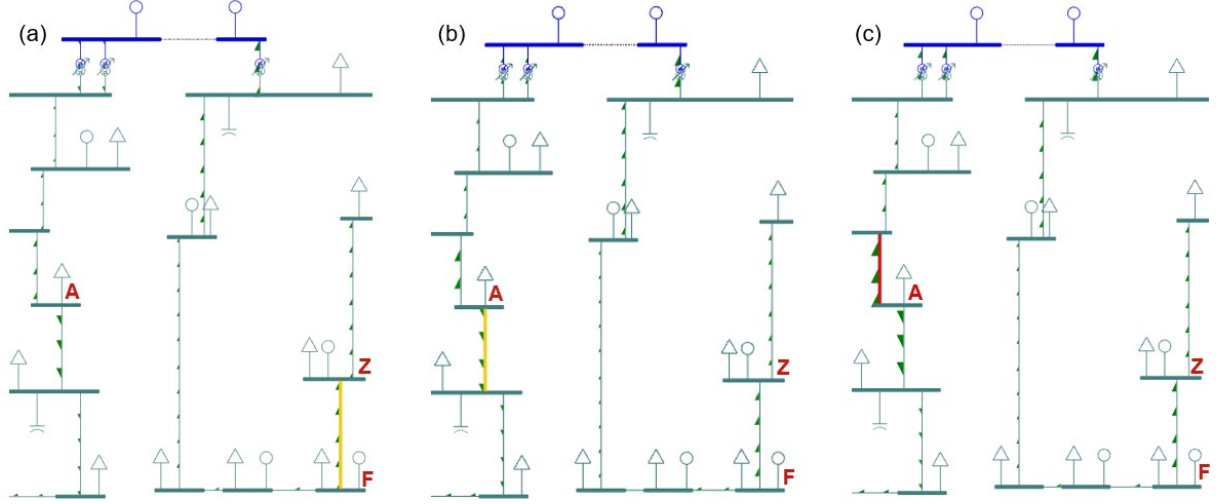


Figure 14: A part of the grid around Bus A showing the effects on the power system for Worst Case Summer after installing new generation. The installed capacity is 137 MW for (a), 229 MW for (b) and 320 MW for (c). The arrows show the direction of power flow in the line, and they are scaled according to the amount of power. The yellow line indicates the line with maximum loading in the grid, and the red line indicates overloading.

In Figure 15, the most critical voltage in the power grid is presented for different levels of installed capacity at Bus A to J. The most critical voltage level is referring to the bus in the power grid with a voltage level closest to either 0.9 or 1.1 per unit. Just as in Figure 12 in Subsection 4.1.1, the red lines represent the limits of 0.9 and 1.1 per unit. It is clear that the voltage level is not affected much by the increase in installed capacity. The bus with the most critical voltage in the power grid has a voltage of around 1.02 per unit. This is the case for all levels of installed capacity, regardless of which bus the power generation is connected to, except for Bus J where the most critical voltage seems to increase up to around 1.04. This is still a neglectable difference.

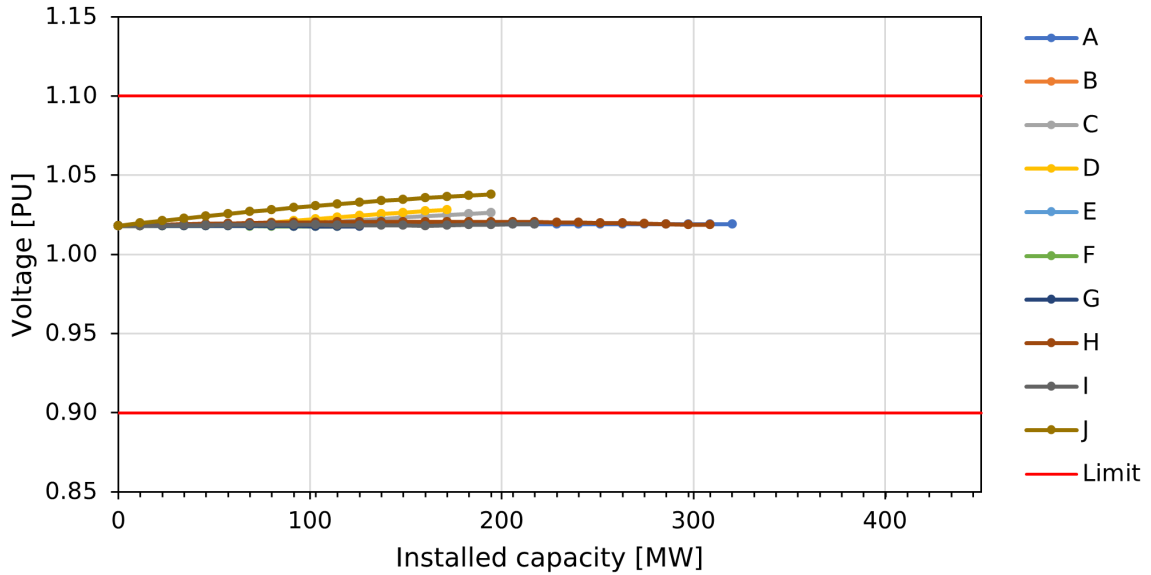


Figure 15: Most critical voltage of all buses in the power grid for Worst Case Summer is presented as a function of the installed capacity at Bus A to J, increasing with a step of 11 MW. The most critical voltage level is referring to the bus in the power grid with a voltage level closest to either 0.9 or 1.1. The red lines represent the voltage limits of 0.9 and 1.1 per unit.

Table 7 presents the assessed hosting capacity of Bus A to J. All assessed hosting capacities are retrieved from Figure 13 since the loading of lines is the limiting factor. Bus A retrieves the highest assessed hosting capacity, while Bus F retrieves the lowest.

Table 7: Assessed hosting capacities for Bus A to J according to Worst Case Summer. The numbers are rounded off.

Bus	Assessed hosting capacity [MW]
A	309
B	206
C	183
D	160
E	126
F	103
G	114
H	297
I	206
J	183

4.1.3 Assessed Hosting Capacity

The results from Worst Case Winter and Worst Case Summer are compiled in Table 8, meaning that the lowest hosting capacity of the worst cases for each bus is chosen. All buses have assessed hosting capacities from Worst Case Summer, except for Bus J which has from Worst Case Winter. This indicates that Worst Case Summer is a more accurate description of the current worst case scenario of the system, however, it is important to investigate both as the difference is rather big between the cases for Bus J. Further, loading of lines is the limiting factor and determines the hosting capacity in all cases. Voltage is never a limiting factor. It is therefore probable that the reason for most buses having assessed hosting capacities from Worst Case Summer, is that the line ratings are much lower during summer. Even if the net load also is lower during summer, the effects from installing new capacity can be straining for lines with a line rating that is generally around 63% of the line rating during the winter. Further, for the deterministic method the new installed capacity is supposed to generate maximum power which might not actually be the case in the summer when the winds are generally weaker, meaning that in practice, Worst Case Summer might be a bit more constraining than Worst Case Winter. However, the same goes for solar power during Worst Case Winter, but solar power accounts for only 30% of the generation.

Table 8: Assessed hosting capacities of the deterministic method for Bus A to J.

Bus	Assessed hosting capacity [MW]
A	309
B	206
C	183
D	160
E	126
F	103
G	114
H	297
I	206
J	80

The lowest hosting capacity is seen when installing generation at Bus J. Bus J and a part of its surrounding grid is presented in Figure 16. For Worst Case Winter, both Bus J and the bus just below show a very high negative load, in other words, generation, of around -70 to -50 MW. For Worst Case Summer, the equivalent values are around -2 to 10 MW, which is significantly lower. The other loads in the area are generally low and unchanged from Worst Case Winter to Worst Case Summer. The generation from Bus J flows downwards in the grid as other large wind power plants are located in the buses just above it, generating much more during Worst Case Winter than Worst Case Summer. With new added generation in the area, one of the lines going downwards becomes overloaded as indicated in Figure 16. This explains why for Bus J, the difference in generation and load in the area between the two worst cases has a greater impact than the difference in line ratings.

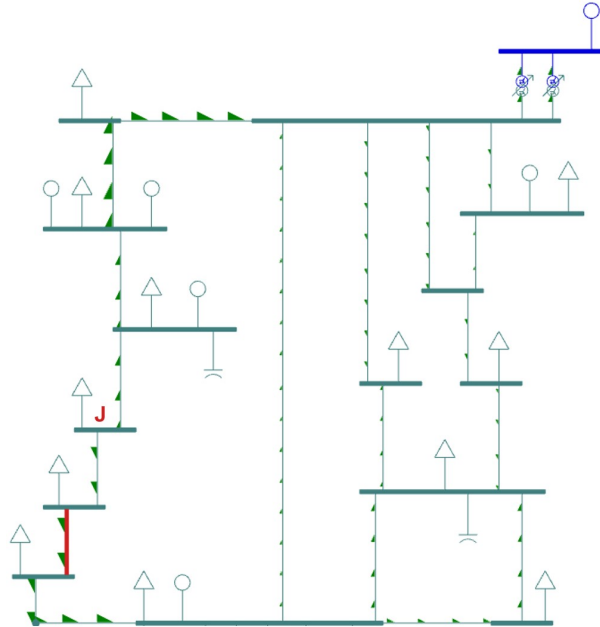


Figure 16: A part of the grid around Bus J showing the effects on the power system for Worst Case Winter after installing new generation of capacity 91 MW, which is above the assessed hosting capacity. The arrows show the direction of power flow in the line, and they are scaled according to the amount of power. The red line indicates overloading.

4.1.4 Risks with Increased Installed Capacity

In Table 9 an installed capacity of 11 MW higher than the assessed hosting capacity from Table 8 in Subsection 4.1.3 is presented. This is presented along with the number of hours during the studied year that the power generation of such a capacity would exceed the assessed hosting capacity, called overgenerating hours, and its corresponding risk. It can be noted that Bus C, D and H have less than 13 hours of overgeneration, which is the limit used for overloading in the time series method, see Subsection 3.3.2. Bus G has the largest risk of 1.27% which corresponds to 111 hours of the studied year with power generation above 114 MW. This does not imply that there will be overloading of lines or voltage violations in the power grid, it only implies that it might occur for up to 111 hours based on the deterministic method results. If overloading of lines or voltage violations occur, it is unknown to what extent.

Table 9: The number of hours with overgeneration is presented for Bus A to J, as well as the corresponding risk. Overgeneration occurs when the power generation is higher than the assessed hosting capacity. The second column presents the increased installed capacity that the calculations are based on, which is 11 MW more than the assessed hosting capacity of the deterministic method. The risk calculations are based on 8 736 hours.

Bus	Assessed hosting capacity + 11 MW [MW]	Hours with overgeneration	Risk [%]
A	320	60	0.69
B	217	20	0.23
C	194	6	0.07
D	172	6	0.07
E	137	89	1.02
F	114	84	0.96
G	126	111	1.27
H	309	12	0.14
I	217	24	0.27
J	91	19	0.22

4.2 Time Series Method

In Figure 17, the maximum loading of lines during the year is presented for different levels of installed capacity at Bus A to J. The red line represents the limit of 100%, and the minor ticks on the x-axis represent each increased step of 11 MW installed capacity. The different sizes of each data point represent how many hours that overloading occurs, this varies between zero hours (which are all below the red limit line) up to 22 hours. Bus G shows 22 hours of overloading in the last simulation, which is much more than 13. This is due to the step of 11 MW between each simulation, leading to many more overloading hours in this case. It can be seen that Bus F has the lowest assessed hosting capacity of 80 MW before exceeding the limit of 13 hours with overloading. The bus with the highest assessed hosting capacity is Bus H with 320 MW. All buses seem to first have a slowly increased maximum loading and then switch to a more rapidly increased maximum loading, except for Bus J where it first decreases. When installing capacity at Bus J, the maximum loading of lines is first decreasing in one line, to later be switched to another line where the maximum loading starts to increase. This switch is causing the elbow seen in Figure 17.

All maximum line loadings seen in Figure 17 occur during the summer months, which agrees with the results of the deterministic method where all occurred during Worst Case Summer except for Bus J which occurred during Worst Case Winter. The reason for the maximum line

loadings occurring during the summer months is that the line ratings are lower during summer than during winter. This is also the reason why the results show loadings of up to 160%, however the loading limit of 160% is never reached as the number of overloading hours exceeds 13 first.

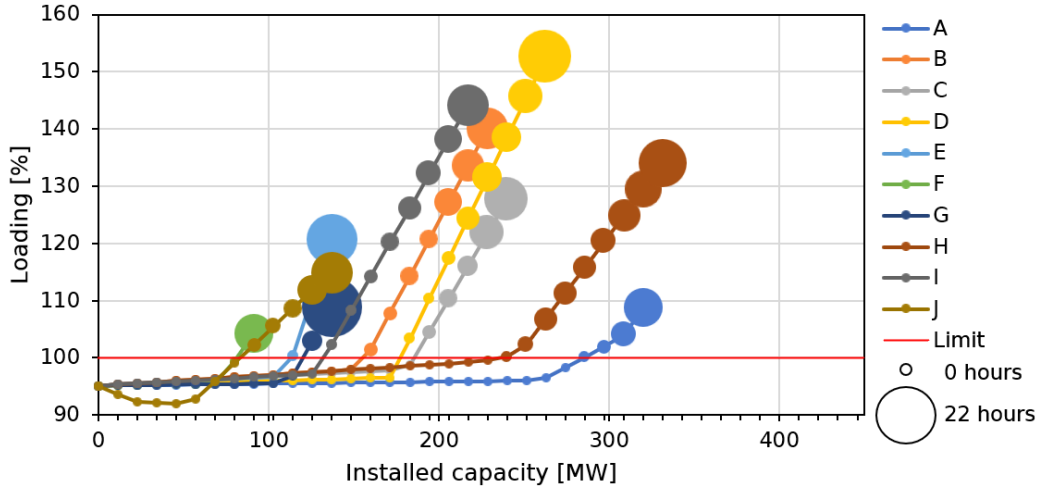


Figure 17: Maximum loading of lines in the power grid is presented as a function of the installed capacity at the bus, increasing with a step of 11 MW, for Bus A to J. The red line represents the loading limit of 100%. The different sizes of the data points represent the number of hours that overloading occurs.

In Table 10, the number of overloading hours for Bus A to J and different levels of installed capacity is presented. Bus H shows overloading for the most number of installed capacities, nine power levels, while Bus F shows for the fewest, only one. This could imply that installing capacity in Bus H is less sensitive since the amount of overloading hours is not significantly increased by the increase of installed capacity, compared to for example Bus F. The bus showing the highest number of hours outside the loading limits is Bus G, with 22 hours, even though the installed capacity is rather low compared to other buses.

In the table, the stars mark where the installed capacity equals the deterministic assessed hosting capacity for Bus A to J. It can be seen that all buses except Bus F show less than 13 hours of overloading for the assessed deterministic hosting capacity. As the assessed hosting capacity is higher for the deterministic method than the time series method for Bus F, the star is marked without any hours at 103 MW. Only four buses, Bus C, D, G and J, have zero overloading hours for the assessed deterministic hosting capacity.

Table 10: Hours with overloading for Bus A to J and different levels of installed capacity. The stars indicate where the installed capacity equals the hosting capacity assessed from the deterministic method.

Installed capacity [MW]	Number of hours with overloading for Bus A to J									
	A	B	C	D	E	F	G	H	I	J
80	0	0	0	0	0	0	0	0	0	0*
91	0	0	0	0	0	13	0	0	0	2
103	0	0	0	0	0	*	0	0	0	3
114	0	0	0	0	1		0*	0	0	4
126	0	0	0	0	6*		5	0	0	9
137	0	0	0	0	18		22	0	1	15
149	0	0	0	0				0	1	
160	0	2	0	0*				0	2	
172	0	2	0	0				0	4	
183	0	4	0*	1				0	6	
194	0	4	2	1				0	7	
206	0	5*	4	2				0	8*	
217	0	10	5	6				0	14	
229	0	14	11	9				0		
240	0		15	9				1		
252	0			11				3		
263	0			19				6		
274	0							6		
286	1							6		
297	2							7*		
309	7*							10		
320	13							12		
332								17		

In Figure 18, the most critical voltage of the power grid during the year is presented for different levels of installed capacity at Bus A to J. The most critical voltage level is referring to the bus in the power grid with a voltage level closest to either 0.9 or 1.1 per unit. The red lines represent the limits of 0.9 and 1.1 per unit. Just as for the deterministic method in Section 4.1, the voltage level is not affected much by the increase of installed capacity and the assessed hosting capacities are determined by the loading of lines. Since the voltage levels are kept inside the limits of 1.1 and 0.9, there are no hours with voltage levels out of bounds. Therefore, the data points in Figure 18 are all the same size, representing zero hours, as shown in the figure's legend. The bus with the most critical voltage in the power grid has a voltage of around 1.07 per unit. This is the case for all levels of installed capacity, regardless of which bus the power generation is connected to.

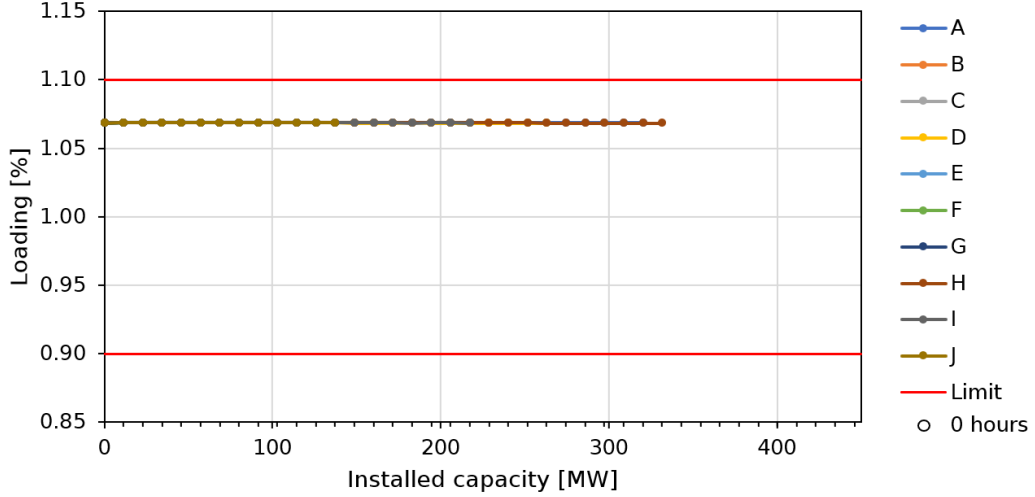


Figure 18: Most critical voltage of all buses in the power grid is presented as a function of the installed capacity at Bus A to J, increasing with a step of 11 MW. The most critical voltage level is referring to the bus in the power grid with a voltage level closest to either 0.9 or 1.1. The red lines represent the voltage limits of 0.9 and 1.1 per unit. The data points are all of the same size, corresponding to zero hours with voltage violations.

In Table 11 the assessed hosting capacity from the time series method is presented. Bus F shows the lowest hosting capacity of 80 MW, and Bus H shows the highest of 320 MW.

Table 11: Assessed hosting capacities of the time series method for Bus A to J.

Bus	Assessed hosting capacity [MW]
A	309
B	217
C	229
D	252
E	126
F	80
G	126
H	320
I	206
J	126

4.3 Correlation Map

The temporal correlation of solar and wind power over the area of the grid case is presented in Figure 19. The solar and wind power are correlated at each location, meaning that no spatial correlations are shown. The correlation is depending on the weather condition on each site, where for example wind speed and shading can vary a lot depending on the terrain. The time resolution is hourly and the correlations are calculated for the year 2020. The locations are 4 km apart from each other. The locations of the buses are marked in the figure. As can be seen, some locations show stronger correlations than other locations. When comparing the buses, Bus J and Bus F are located in areas with the highest and lowest correlation, respectively. However, the differences are very small and the area as a whole is showing weak positive correlations, implying that solar and wind power are not that complementary in this particular area. The scale for correlation goes from -1 to 1, where a value around 0 indicates no correlation. For a high

complementarity, a strong negative correlation would be better, meaning a value closer to -1. With a strong negative correlation, the chance that the two power sources generate at maximum capacity at the same time is lower. In terms of hosting capacity, the hosting capacity could probably be increased for lower risk in the areas where the complementarity is higher. Further, it is expected that the difference between the deterministic method and the time series method is bigger with a higher complementarity, as only the time series method considers correlations.

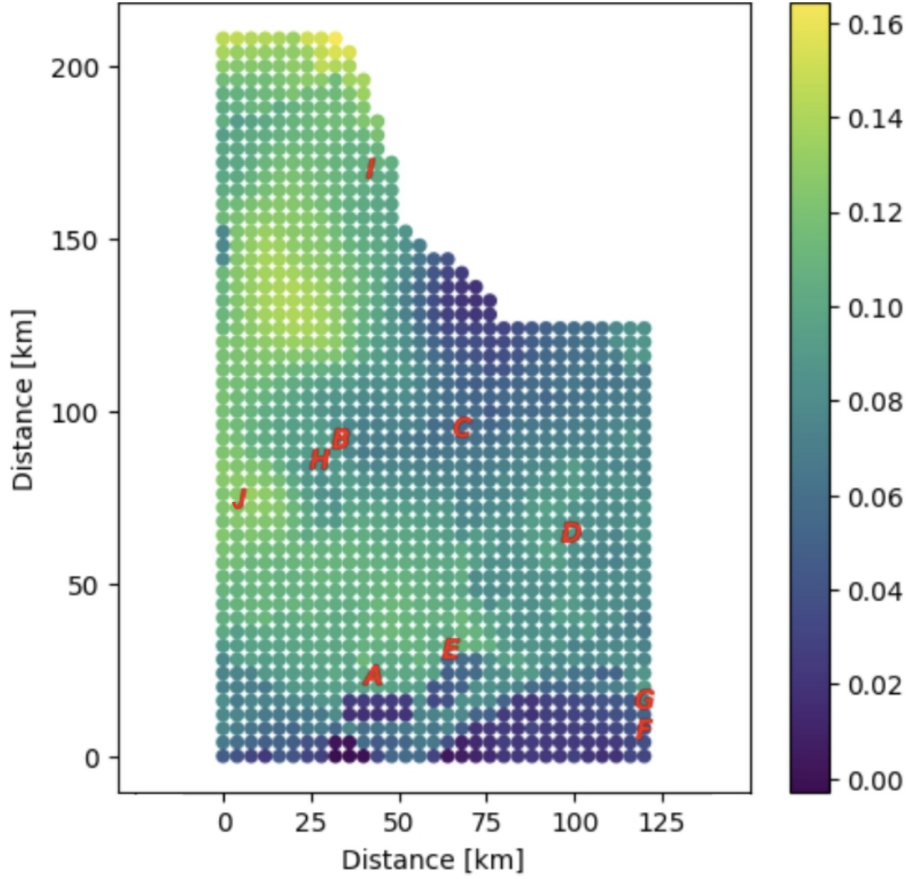


Figure 19: The temporal correlation of solar and wind power in the area of the grid case. The locations are selected from a 4×4 km² distance. Buses A to J are marked in red text. A higher value, or brighter colour, indicates a stronger positive correlation, which indicates a low complementarity.

The values seen in Figure 19 differ from the values mentioned in Subsection 2.3.2. Therefore, the uncertainty from the used power law exponent is examined further. Since Visual Crossing has available data on wind speed at 100 m for 2022, the chosen power law exponent in this thesis can be compared with the extrapolation used by Visual Crossing. The correlation is calculated for one location based on the 2022 wind speed at 100 m from Visual Crossing and compared to the correlation calculated for the same location based on the 2022 wind speed at 10 m which is extrapolated to 100 m with the power law exponent. The correlation coefficient based on wind speed at 100 m is calculated to be -0.02, while the correlation coefficient based on the extrapolated wind speed is calculated to be 0.14. This difference is noticeable and highlights the uncertainties caused by having an averaged power law exponent for the whole grid case area.

4.4 Compilation of Hosting Capacities and Correlations

In Table 12, a compilation of the assessed hosting capacities from both the deterministic method and the time series method is presented, together with the correlation coefficients at the buses. It is seen that the time series method results in a higher or the same assessed hosting capacity for most buses. The difference between the methods are biggest for Bus D in absolute numbers, but equally big for Bus D and J in relative numbers. Three buses, Bus A, E, and I, show equal results from both methods. Bus F is the only bus showing a lower assessed hosting capacity from the time series method. It is seen in Subsection 4.1.2 that Bus F is located in an already strained part of the grid, where generation added to Bus F imposed a fast increase of loading of Line F–Y and resulted in the lowest assessed hosting capacity for Worst Case Summer. The grid shows vulnerability around Bus F during Worst Case Summer and probably during all months with summer line rating. It is likely that a different hour during summer is the actual worst case for Bus F, leading to an inadequate deterministic hosting capacity when assessing it based on Worst Case Summer. This is probably because the net power output used to find Worst Case Summer does not accurately indicate the hour with the highest power generation in the sensitive grid area around Bus F.

The correlation coefficients imply that the assessed hosting capacities of the time series method should be higher than the deterministic method, regardless of the bus. This is since some complementarity between wind and solar power occurs and is taken into account in the time series method only. The correlation coefficients are not in direct relation to the change in assessed hosting capacity between the deterministic and time series method. For example, it would be reasonable if Bus J with the highest correlation coefficient has the lowest change in assessed hosting capacity. However, the correlation coefficients differ only marginally. As the correlation coefficients are similar for all buses, while the assessed hosting capacities differ between the buses, it can be concluded that the correlation coefficients are not the reason for the variations in assessed hosting capacities between the different buses.

Table 12: Comparison of hosting capacities of the deterministic method and the time series method for Bus A to J. The correlation coefficients of all buses are also presented.

Bus	Assessed hosting capacity, deterministic method [MW]	Assessed hosting capacity, time series method [MW]	Change from deterministic to time series method [%]	correlation coefficient [-]
A	309	309	0.0	0.10
B	206	217	5.6	0.09
C	183	229	25.0	0.06
D	160	252	57.1	0.09
E	126	126	0.0	0.11
F	103	80	-22.2	0.04
G	114	126	10.0	0.08
H	297	320	7.7	0.09
I	206	206	0.0	0.11
J	80	126	57.1	0.13

In Table 13 the number of overgenerating hours when installing 11 MW more than the assessed hosting capacity of the deterministic method, and the number of overloading hours from the time series method is summarised, see Table 9 and 10. Note that Bus F has a value of 48 hours in Table 13 but has no value in Table 10. This is, as stated in Section 4.2, due to the assessed hosting capacity being higher for the deterministic method than for the time series method for Bus F. To retrieve this value a time series simulation for an installed capacity of

103 MW is performed, resulting in 48 hours of overloading.

The number of overgenerating hours is compared with the number of overloading hours retrieved from the time series method when installing the same capacity. It can be seen that the number of overloading hours is less than the overgenerating hours for all buses. This is expected since, as described in Subsection 4.1.4, the risk assessment of the deterministic method does not imply anything about overloading. The risk assessment only implies that overloading might occur for up to the number of overgenerating hours.

Table 13: A comparison in risk for the same installed capacity, with results from Table 9 and Table 10.

Bus	Assessed deterministic hosting capacity + 11 MW [MW]	Hours with overgeneration according to risk assessment	Hours with overloading according to time series method
A	320	60	13
B	217	20	10
C	194	6	2
D	172	6	0
E	137	89	18
F	114	84	48
G	126	111	5
H	309	12	10
I	217	24	14
J	91	19	2

5 Discussion

In this chapter, the method choices and results are discussed.

5.1 Methodology

Throughout this study many simplifications and choices have been made in all parts; from retrieving weather data to modeling power data to performing different simulations in PSS/E to finally analysing the results. These choices are here discussed.

5.1.1 Renewable Power Generation Modeling

When modeling the solar and wind power, effective and accurate methods and components were chosen, to not underestimate the generated power. This applies to for example the choice of inverter or wind turbine. These choices can be assumed to have little impact on the accuracy of the modeled power. That being said, the biggest uncertainty in this aspect would be the use of a power law exponent for modeling wind power generation. An average power law exponent was used for all locations which brings uncertainties. It would likely be more accurate to use specific power law exponents for all locations so that the different types of terrain are taken into account. Also, the power law method as such comes with uncertainties. However, as mentioned in Subsection 2.1.1 there is no easy way to model wind speed at different heights, many methods exist but all bring various uncertainties.

The DC/AC ratio of the solar power inverter is important as it can adjust the solar power generation pattern to increase its capacity factor. This is done by curtailing the maximum capacity to a lower level and thus causing the solar power plant to reach its maximum capacity more often. This thesis is based on the assumption of that different renewable energy sources complement each other by not reaching their total maximum capacity as often as they would separately. A too high DC/AC ratio would have an effect on this fundamental assumption and could result in other estimates of the hosting capacity. However, the chosen ratio is based on the current market which enhances the applicability of this thesis for a DSO.

Similar behaviour can be applied for wind power plants if the installed capacity is higher than the highest allowed or most economical injected power. The plant owner then uses active curtailment to reduce the generation to the contracted injected power, which causes the maximum injected power to be reached more often. This is not applied in this thesis but would have the same effects as a high DC/AC ratio has on solar power plants.

The ratio between solar and wind power of the installed capacity is an important factor in estimating the hosting capacity. It was assumed most relevant for this thesis to use the most optimal ratio in regards to an even power output, as this would show the biggest potential in increasing assessed hosting capacity by considering complementarity. The choice to have a 3-to-7 ratio of solar power to wind power was based on conclusions from Widén [5] that this would give the most even capacity over the year, but this was on a national scale and the more recent work by Lindberg [14] argues that a lower ratio of wind can be preferable in regards to the reliability of power generation. On the other hand, Widén [5] states that hourly fluctuations are always bigger with more solar power.

In practice, this ratio varies on project-by-project basis. It can be dependent on aspects such as available land, energy assessments for solar and wind power of the site, and others. This ratio will affect the assessed hosting capacities since solar and wind power have different generation

patterns. A significant difference is that a wind power plant reaches its maximum capacity more often than a solar power plant, which is indicated by their respective capacity factors. However, this is dependent on the operation of the power plants, for example, which DC/AC ratio is used for the solar power plant. Also, solar power generation has very clear seasonal and diurnal patterns with no power generation during the night and very little during the winter in Sweden. The results of this thesis indicate that the summer months limit the hosting capacities rather than the winter months. If the 3-to-7 ratio is tilted in favour of solar power, it could either result in a lower assessed hosting capacity due to the summer months being limiting or a higher due to wind power plants having higher capacity factors. This is situation-dependent and could be interesting to investigate further. However, for comparing the results of the different hosting capacity methods, the set ratio is not of significant importance.

5.1.2 Power System Analysis

Regarding the power system analysis and the simulations in PSS/E, limitations had to be made as a full power system analysis is an extensive process in regards to time, knowledge and experience. For example, not only thermal loading of lines and voltage but many other performance indices can be investigated in a full power system analysis. Also, dynamic simulations and contingency analyses can be performed besides the steady-state analysis. But as the power system analyses in this thesis are performed mainly to compare different hosting capacity methods, the chosen studied aspects and steady-state simulations should be sufficient for the purpose of this study.

An inherent limitation of the power system analysis, is the limited data set. The power generation and load data used in the time series method is of hourly resolution, meaning that the hourly data shows an average for that hour. This data resolution is quite coarse, which might impact the results. Overloading and voltage violations may occur within shorter time frames, and in such cases, they may not be accounted for. However, higher resolution data require significantly more computational time. Also, the available historical data from Ellevio, Visual Crossing [63] and SMHI STRÅNG [64] were given in hourly resolution. This subject is investigated by Ludwig et al. [79] in a solar power context. The main objective of the study was to assess the needed curtailment to maintain a stable power system, and this was slightly underestimated using hourly data instead of minute data. The differences were however very small, indicating that hourly data should give rather accurate results. Lindberg et al. [80] also discuss this and state that wind speed variations on small time scales are out of interest from a power system perspective as these are compensated for in the machinery of the turbine.

The power grid case is also limited in terms of size, number of buses, number of connected machines, and others. There might be issues with using real data from Ellevio based on a real power grid when the power grid used for simulations in PSS/E is simplified. These possible issues are difficult to overlook. Due to limitations in the number of connected machines, some power generation is simulated as distributed generation in connection with a load instead of a power generating machine. This entails a reduction in voltage regulation from the machines, but as the voltage variations are unproblematic in this study, it should not affect the accuracy of the results.

5.1.3 Hosting Capacity Methods

In this thesis, two methods of which one is a deterministic method and one is a time series method are compared. However, the deterministic and time series methods used in this thesis are not representative of all deterministic and time series hosting capacity methods, as the conduction of those can differ substantially.

For both methods, a step of 11 MW is used to increase the installed capacity of new power

generation and assess hosting capacity. This step is rather large in comparison to the actual generation on different sites in the studied area. It gives a range of error for the assessed hosting capacity, as the actual hosting capacity can be found anywhere between the upper and lower limit of each capacity step of 11 MW. However, as mentioned in Subsection 2.5.2, there exists no such thing as an actual hosting capacity. All assessment methods are connected to a range of error or risk. Further, this thesis does not aim at retrieving accurate hosting capacities but compares different methods to do so. Nevertheless, this step size can affect the accuracy of the comparison between the studied methods as the general accuracy deteriorates.

For the deterministic method, the choice of analysed hours that should represent the worst case scenarios is critical. It requires experience in the area and an accurate data set to be able to identify adequate worst case hours. Using wrong hours, assuming that they are the worst cases, leads to an overestimation of the hosting capacity. In this thesis, two worst cases were assessed, one for the winter season and one for the summer season. They were chosen based on the net power output from the grid as a whole. The net power output can, but does not necessarily have to, show strained hours when the generation is higher than the load. Its main drawback is that it does not consider how the power generation and its closely located loads vary over the grid. Overloading and voltage violation happen locally and should therefore be assessed locally. It is precarious to try to find the hours when this might occur by just looking at the grid as a whole. However, the main strengths of the deterministic method are its simplicity and speed, and these strengths would be set back by a too advanced method to find the actual worst cases, or by analysing too many cases.

The time series method has no need of assessing such cases as all hours from available data are analysed. Thus, it is important that the available data includes adequate worst cases that can occur in the grid, which is difficult to verify. In this thesis, 8 736 hours from the year 2020 are analysed. This amount of data is insufficient for retrieving accurate results, as for example weather conditions vary from year to year. Using a too small data set in a time series method can lead to an overestimation of hosting capacity.

5.2 Results

In the upcoming section, the results from the deterministic and time series method are discussed and compared to each other. The methods are also discussed and compared from a perspective of risks and reliability and applicability of results.

5.2.1 Hosting Capacity Methods

As mentioned in Subsection 2.5.2, the deterministic method is perceived as conservative and results in a pessimistic estimation of the hosting capacity, assuming that the worst case is correctly identified. The time series method is perceived as possibly more accurate, but also more risky as the new power generation is varied and not assumed to be at maximum capacity. It is therefore expected that the time series method would result in higher assessed hosting capacities, which was also seen in several buses. In one bus, the opposite was seen. This indicates that for this bus, the deterministic method was not accurate as the chosen worst case hours did not reflect the limitations of the grid surrounding this bus.

In Table 10 it is seen that for six buses, the number of overloading hours for an installed capacity of the assessed deterministic hosting capacity exceeds zero when applied to a time series method. These buses would thus have a lower hosting capacity from the time series method than from the deterministic method if no overloading hours were accepted in the time series method. This clearly implies that the worst case hours used in the deterministic methods are locally

inaccurate for several buses, not only Bus F, as worse hours are analysed in the time series method. This highlights a significant drawback of the deterministic method, which is that it is difficult yet highly critical to find accurate worst case scenarios to analyse. CIGRE [8] also highlights this in its technical report on worldwide optimal power system planning. If the worst hour is not accurately identified and analysed, the hosting capacity will be overestimated. This questions the perceived conservativeness of the deterministic method, concerning the expectation of the hosting capacity being underestimated rather than overestimated.

Regarding risks with increasing installed capacity over the deterministic hosting capacity, Table 9 shows that only three buses have a risk of overgenerating for less than 13 hours. However, overgeneration does not necessarily imply overloading. In Table 13 it is seen that seven buses show overloading for less than 13 hours. This means that increasing the installed capacity 11 MW above the assessed deterministic hosting capacity, leads to manageable risks for seven out of ten buses. As all buses show a lower number of overloading hours than overgenerating hours, the overgenerating hours can be used as upper limits for overloading hours. However, it is important to consider the choice of worst case hours when assessing the risks. If the worst cases are correctly identified, then the risks based on overgenerating hours presented in Table 9 can be considered as upper limits. But if the worst cases are wrong, the risk of overgeneration can be either higher or lower. With a conservative and reliable method to find worst case scenarios, the risk assessment based on overgeneration can be a fast and simple way to assess the risks with increasing installed capacity over hosting capacity. It can save a lot of computational time compared to performing a full time series method to assess overloading hours.

The reliability of the results from the deterministic method is as mentioned mainly connected to identifying the worst case scenarios. The reliability of the results from the time series method is mainly connected to the modeling of the power generation. In order to accurately model the power generation, accurate weather data and models are also needed. For both methods, also the need for an accurate, large enough data set for the power system is important for reliable results. For the deterministic method, this relates to being able to adequately assess both worst case scenarios and the current condition of the grid. The time series method relates to this as well, but also to being able to cover for example load and weather variations. Thus, the importance of a large enough data set could be extra important for the time series method.

The results of the time series method show that all overloading of lines occurs during the period of summer line ratings. This implies that the line rating has a significant impact on the assessed hosting capacity. It would therefore be interesting to implement DLR in hosting capacity methods. If the overloadings occur during nights or other periods of time with less extreme weather conditions than the ones assumed for summer line ratings, the hosting capacity could be increased using DLR.

5.2.2 Comparison with Correlation Map

A difference between the methods is that the time series method naturally considers the temporal correlations between different power sources and load, which could lead to a higher assessed hosting capacity for the time series method if the correlations are strongly negative, implying a high complementarity. It is seen in Table 12 that complementarity between solar and wind power in this specific grid case exists but is low with correlation coefficients around zero. This speaks for the time series method having higher hosting capacities which is also the case for the majority of the buses.

It should be noted that the complementarity between solar and wind power is probably not the single reason for the assessed hosting capacities being higher for the time series method than for the deterministic method. There are mainly three other aspects playing a part in this difference. The first aspect is the fact that the time series method allows up to 13 hours of overloading. If fewer overloading hours would have been accepted, the difference between the

assessed hosting capacities from the two methods would be smaller. The second aspect is the choice of worst case hour of the deterministic method. If the worst case hour would have been correctly identified, the difference between the assessed hosting capacities from the two methods would be smaller. Finally, a certain correlation coefficient does not guarantee that no hours of coinciding maximum power generation will occur, meaning that this can still happen during the year of simulation in the time series method.

The correlation coefficients vary marginally between all buses, but the hosting capacities vary significantly. Further, the changes in correlation coefficient between the buses do not relate to the change in assessed hosting capacity between the deterministic and time series method. The difference between the methods is zero for three buses, and these buses have approximately the same correlation coefficients as the two buses with the greatest relative difference. This can be partly explained by the small differences in correlation coefficients in the area, but it also indicates that the complementarity of a location is of small importance for the assessed hosting capacity. It is likely that other local conditions, such as local grid structure, loads and existing power generation, have a stronger impact. This is also highlighted by the results from the deterministic method, see Table 8, where the hosting capacity varied widely despite considering no complementarity.

5.2.3 Study Validity

It is clear from the results of this thesis that the voltage level plays a less important role in comparison to the loading of lines. According to Bollen et al. [81] and the general experience at Ellevio, the loading of lines is the limiting factor when comparing loading of lines and voltage levels of buses in regional grids, which speaks for that the results, in that aspect, is reasonable.

This thesis is mainly based on modeled data. Jurasz et al. [19] state that there is little research regarding how complementarity between actual measured data might differ from model-based data, and argue that there might be some complementarity based on model choices rather than actual circumstances when using modeled data. Similarly, Lindberg et al. [80] warn about misleading correlation coefficients due to not enough accuracy and comparability of data. Specifically, they state that using the power law to extrapolate wind speeds to higher heights can lead to incorrect values. They also highlight the need of validating modeled power data with real power data. The wind power in this thesis is visually validated against historical wind power generation data from Ellevio. The validation is presented in Subsection 3.1.2 and argues that the wind power modeling is accurate. However, this data is only compared for a few locations where wind power generation exists. The remaining locations in the correlation map are assumed to be accurate based on the validation from these locations, which brings uncertainties. As for solar power, there is no way to adequately validate the modeled power data with historical data.

Another way to validate the modeling of power generation is to compare the so-called capacity factors of the modeled power generation with the ones mentioned in Section 2.1 and 2.2. It is stated in Section 2.1 that the capacity factor for wind power plants in the middle-southern part of Sweden is around 27.7%. The locations of the ten buses A to J have varying capacity factors between 31.8% and 9.1%, resulting in an average capacity factor of 19.7%. It can be considered reasonable that the average capacity factor is lower than 27.7% since the ten buses were chosen randomly which entails risks of non-optimal weather and site conditions for wind power generation. As stated in Section 2.2, the capacity factor for solar power plants usually varies between 15 and 35%, and for solar power plants in Sweden it is around 11%. The capacity factor of Bus A to J varies from 14.2% to 17.2% resulting in an average of 15.6%. These are considered reasonable values since it is within the range of 11 and 35%, the reason for the capacity factor being higher than 11% is probably due to the high DC/AC ratio. It could be expected that the buses with the highest capacity factors of solar and wind power would result in the lowest hosting capacity from the time series method since there would be high power generation more

often which could result in reaching loading limits faster. This is not the case though, which argues for other aspects playing a bigger role, for example how the power grid is structured in terms of lines, existing loads, generators and other components.

The results from the correlation map in this thesis do not show the expected results when compared to what is stated by Lindberg [14]. Lindberg states that the correlations are around -0.1 to -0.2 while this thesis shows results of around 0.0 to 0.16. The reason for this is probably due to the use of power law when extrapolating wind speed from 10 m to 100 m. The power law exponent used in this thesis is based on the average power law exponent of a number of equally distributed locations in the power grid area, see Subsection 3.1.1. With wind speed data at 100 m from Visual Crossing, the resulting correlation for one location was -0.02, compared to 0.14 using the average power law exponent, as described in Section 4.3. This indicates that using an average power law exponent might not be accurate for calculations of wind speed at 100 m. Note however that the correlation coefficient of -0.02 is still far from Lindberg's values of -0.1 to -0.2, which emphasises how modeled power generation is in all cases an estimation which can cause uncertain results. On the other hand, as discussed before, the modeled wind power data is visually validated against historical data. Solar power is not validated to the same extent and could also be the cause of unexpected correlation coefficients.

5.2.4 Applicability of Results

The method and results of this paper can be applied by other DSOs to estimate the hosting capacity in their power grids. There are however some considerations that need to be taken into account. An important aspect for a DSO is the behaviour of the grid customers, which is not fully considered in this thesis but might have a big impact on its applicability. Grid customers, for example, renewable power plant owners, are usually aware that the hours with power generation at maximum capacity are few. Therefore they might use for example high DC/AC ratios, wind power curtailment or energy storage to decrease their maximum injected power to an economically optimal level. These measures reduce the complementarity of solar and wind power and increase the instances when both power sources generate at maximum capacity. As this reduces the variability of the power generation, it would make renewable energy sources more similar to traditional, and therefore reduce the need of looking into other hosting capacity methods than the traditional deterministic. Further, hybrid power plants might play a bigger role in the future. For these, no complementarity can be considered when assessing the hosting capacity as the hybrid power plant owner usually already has considered this when applying for a level of allowed injected power.

The generation from solar and wind power plants is in this thesis modeled based on historical weather conditions which are not entirely representative of future power generation. Jurasz et al. [19] mention that climate change will most likely affect renewable energy sources as well as their complementarity in the future. This suggests that historical data can be difficult to use when investigating future investments and implementations of solar and wind power plants. Forecasting methods that consider climate change might be useful to predict weather conditions and thereby power generation. However, the aim of this thesis is to compare the hosting capacity methods, thus no definite hosting capacities are retrieved and the use of historical data is in this matter sufficient. But for grid owners considering a time series method, one should perhaps take into account the effects of climate change concerning the complementarity of renewable energy sources.

When it comes to the practicality and applicability of the methods for a DSO, the deterministic method is significantly faster and requires less data as no modeling of power generation is needed. This also reduces the uncertainties, as modeling power generation comes with many assumptions. However, the deterministic method still requires enough data to at least identify the worst case scenario. The time series method is more complicated in its procedure, but it gen-

erates straightforward results and requires no pre-simulation analyses, such as identifying worst case scenarios which the deterministic method requires. The time series method also generates more detailed results as each hour is analysed, which can give a more profound understanding of the power system. It also gives the opportunity to further analyse some critical hours and possibly understand why they are critical, which can be important for adequate power grid planning. The time series method in this thesis allows for up to 13 hours of overloading, which can induce risks if the specific power grid or grid owner does not have the prerequisites to handle this amount of overloading.

6 Conclusions and Future Studies

The final chapter of this thesis presents the main conclusions and some proposals for relevant future studies.

6.1 Conclusions

It is concluded that the assessed hosting capacity differs between the hosting capacity methods for most buses, and for a few buses the difference is significant. The assessed hosting capacities from the time series method are expected to be higher than the ones from the deterministic method since the time series method considers complementarity and intermittency of solar and wind power. This is the case when installing solar and wind power in the majority of the buses. However, complementarity may not be the single reason for this result. It is probably also due to the allowed number of overloading hours. For a few buses, the hosting capacity of the time series method is the same or lower than that of the deterministic method. These unexpected differences between the two hosting capacity methods are probably due to inaccurately chosen worst case hours.

According to this thesis, it can be concluded that the complementarity between solar and wind power in the area is low. The calculated correlations have many accompanying uncertainties though, which makes it difficult to draw conclusions on how the complementarity between solar and wind power affects the assessed hosting capacities. However, as the complementarity is almost the same for all ten locations, and the hosting capacity differs widely between the locations, the complementarity has no or small effect on the differences in assessed hosting capacities for different locations. It is more likely that the local conditions of the grid are the influencing factor. Further, the differences in assessed hosting capacities between the two methods can not be set in relation to the levels of complementarity. It is likely that these differences instead depend on hourly variations in the time series method.

The risks concerning overloading hours are compared between the different methods. It can be concluded that assessing the overgenerating hours using the deterministic hosting capacities, is a simple and fast way to find the maximum number of overloading hours without fully performing the time series method. However, it is important that the deterministic hosting capacities are adequate and that the analysed worst case scenarios for the deterministic method are reflective of the worst cases for the grid. It can further be concluded that increasing the installed capacity with one step over the assessed deterministic hosting capacity leads to manageable risks for seven out of ten buses in this grid case. This indicates a potential for examining increased installed capacity further for DSOs, in order to possibly accept more renewable power without imposing too much risk.

In this thesis, the reliability of results is lower for the deterministic method than for the time series method, even if the deterministic method usually is considered more conservative. This is due to the difficulties of correctly identifying the worst case hours in the grid. A more solid method to identify the worst cases is needed if a deterministic method similar to the one in this thesis is to be used. Specifically, a solid and simple method to identify the worst cases locally for specific buses is needed. To our notice, this is not used widely today and would therefore need to be developed. Such a method can improve the prospects of the deterministic method in providing a conservative estimate of the hosting capacity. The time series method includes more scenarios and more information which in this case increases the reliability of results, but it is a method that uses historical data of the variations of load and power generation, which will not reflect all possible future scenarios. The time series method also considers the possible

complementarity between different power sources, and even if this might be more accurate, it induces risks compared to considering coinciding maximum generation from both sources, as this still can occur. Also, measurements to reduce maximum capacity and reach it more often, such as energy storage, high DC/AC ratio or curtailment, might become more common in the future and further induce risks from considering complementarity.

Based on the results in this thesis, it is concluded that the results of the time series method are more reliable than those of the deterministic method. The time series method is preferable as it is both more reliable as no mistakes can be made in identifying accurate worst case scenarios, and more realistic as it takes complementarity and variations over time into account. However, the time series method also has drawbacks and is not always possible to use, due to for example lack of data. All in all, the development of hosting capacity methods is important and necessary to be able to allow more connection of renewable power generation without affecting a secure power supply.

6.2 Future Studies

The different hosting capacity methods of today all have drawbacks and uncertainties, and to have a secure and efficient power system it is important to develop this area. In the future, the methods should be adapted to the current power systems and their conditions and to do this, research to find a common best practice should be conducted. Some suggestions on topics for this are here presented.

Dynamic Line Rating (DLR) is interesting to investigate in regards to time series methods, as for example high wind power generation and high line rating could show a strong positive correlation and therefore be of relevance in areas with much wind power generation. The results in this thesis highlight the strong influence of line rating for the assessed hosting capacity, which further emphasises the need for DLR implementation.

The use of energy storage is a growing trend that also needs to be included in coming research. Energy storages owned by District System Operators (DSOs) have the potential for improving the hosting capacity by reducing overloading.

This thesis has investigated the impact of temporal correlation over the power grid. The importance of spatial correlation over a grid could also be of relevance when assessing the hosting capacity and of interest to investigate. To do so, one could investigate new power generation installed to several dispersed buses and evaluate the resulting hosting capacities, as well as spatial correlations between the buses.

Based on the results in this thesis, a method for finding a maximum value of possible overloading hours for an installed capacity, by assessing its overgenerating hours, has the potential to be a convenient extension of deterministic hosting capacity methods. It would be interesting to develop this further.

This thesis has highlighted the importance of identifying accurate worst case scenarios in the grid when using deterministic methods. Thus, a suggested future study is to develop solid methods for doing so. This includes both worst cases for the entire power grid, as well as more local worst cases. Local worst cases can be of importance since it has been apparent that the structural differences in the power grid, such as components, local loads and power generation, have a significant impact on both the identified worst case and the assessed hosting capacity based on it. A more reliable method for identifying the worst case could make any deterministic method a more reliable and convenient hosting capacity method.

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