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Geographical Competitiveness for Powering Datacenters with Renewable Energy

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Abstract

In this paper we analyze the feasibility of using renewable energy for powering a data center located on the 60th parallel north. We analyze the workload energy consumption and the cost-energy trade-off related to available wind and solar energy sources. A wind and solar power model is built based on real weather data for three different geographical locations, and The available monthly and annual renewable energy is analyzed for different scenarios and compared with the energy consumption of a simulated data center. We show the impact different data center sizes have on the coverage percentage of renewables, and we discuss the competitiveness of constructing datacenters in different geographical location based on the results.

Keywords Green energy, datacenter, simulation, geographical locations

I. INTRODUCTION

The global energy price and tighter restrictions on energy production has led to a higher utilization of green energy, which is produced from completely carbon neutral sources. One of the latest trends in reducing the carbon footprint of data centers is powering the datacenters with renewable sources of energy. This course is being encouraged by the advances of renewable technologies and continuously decreasing renewable energy costs. Renewable energy sources have become an interesting option for large scale server farms, and initiatives such as Google Green[1] and Facebook Sustainability[2] have been taken to decrease the carbon footprint both for ecological and monetary reasons. Recently, the location of large scale server farms has shifted to the nordic countries above the 60th parallel because of a cooler climate, which in turn reduces the cooling costs for such datacenters. The energy required for computation and the infrastructure must, however, be delivered from the electric grid, preferably generated by renewable energy. This poses a challenges for northern countries because of the large variation in available solar energy throughout the year. While the summer period provides from 18 to 20 hours of sunlight, the winter period provides merely a few hours – this from a very shallow angle of reflection. The lack solar energy can be compensated with other sources such as wind energy, but the total cost of powering the data center must be sufficiently low in order to stay competitive to other geographical locations.

We present in this paper a thorough analysis of the feasibility of powering large scale datacenters in geographical locations above the 60th parallel north with renewable energy. The analysis contains simulations of different datacenters executing various workloads and the requirements in green energy production for different geographical locations. In contrast to previous work we compare different geographical locations in terms of both available renewable energy and required datacenter capacity for satisfying the end user. We also provide an a competitiveness factor between different geographical locations for the feasibility of powering a datacenter with renewable energy sources.

II. RELATED WORK

Real implementations of green data centers. Researchers at Rutgers University [9] present Parasol and GreenSwitch, a research platform for a green data center prototype. It consists of GreenSwitch software running over a real hardware data center, Parasol. Its aim is reducing the total data center cost by properly managing workloads and available energy sources for maximum benefits. It also studies the space requirements and capital costs of self-generation with wind and solar energy. Similarly, [18] presents Blink, a physical implementation of using intermittent power to supply a cluster of 10 laptops by two micro wind turbines and two solar

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[1] https://www.google.com/green/
[2] https://sustainability.fb.com/en/

panels, supported by small 5-minute energy buffer batteries. HP Labs has built a 4 servers data center partially powered by solar panels [6]. The data center is powered by the grid when no solar energy is available. In contrast to these real implementations, we simulate different scenarios to adapt different data center sizes and workload, with thousands of physical and virtual machines. Thus, we have a broader view of the impact they have on the amount of required renewable energy.

Simulators for green data centers. Michael Brown and Jose Renau present ReRack [2], an extensible simulation infrastructure that can be used to evaluate the energy cost of a data center using renewable energy sources. It also includes an optimization module to find the best combination of renewable sources that minimize cost. Yanwei Zhang et al [24] have developed GreenWare, a middleware system that conducts dynamic request dispatching to maximize the percentage of renewable energy used to power a network of distributed data centers, based on the time-varying electricity prices and availabilities of renewable energy in their geographical locations. It also considers different prices per kWh solar and wind energy have in different geographical data center locations, distributing the workload accordingly for lowest overall cost possible. In our study, instead, we do not develop a simulator but focus on studying the relation between quantity of renewable energy sources and data center energy consumption for a certain coverage with renewable. We take into consideration different workload scenarios.

Managing the workload in green data centers. Rutgers University proposes GreenSlot [8], a parallel batch job scheduler for a data center powered by a solar panel and the electrical grid (as a backup). It can predict the amount of solar energy that will be available in the near future, and schedules the workload to maximize the renewable energy consumption up to 117% while meeting the jobs' deadlines. Likewise, GreenHadoop [10], a GreenSlot successor, represents a MapReduce framework seeking to maximize the renewable energy consumption within the jobs' time bounds. Ghamkhari et. al. [7] offer an optimization-based workload distribution framework for Internet and cloud computing data centers with behind-the-meter renewable generators in order to save energy. This is achieved by better resource utilization taking into account several impacting factors like computer servers' power consumption profiles, data center's power usage effectiveness, availability of renewable power at different locations, price of electricity at different locations. Aksanli et al. [1] design a new data center job scheduling methodology that effectively leverages green energy prediction, which enables the scaling of the number of jobs to the expected energy availability. They develop a discrete event-based simulation platform for applying this methodology in a data center consisting of hundreds of servers. Liu et al. [14] evaluate the impact of geographical load balancing and the role of storage in decreasing the brown energy costs. The authors also suggest the optimal mix of renewables to power Internet-scale systems using (nearly) entirely renewable energy. They use homogeneous servers and 1 week HP Labs workload traces, while we base our simulations on heterogeneous sets of servers and a more generalized workload trace, which is automatically generated by uniformly distributed time, duration and type of the user requests. Beside this, their selected data center countries represent locations with high solar energy production, but we give contribute in studying the renewable energy capacity on the 60th parallel north where sun intermittent nature is more significant. Workload management is not part of our analysis in this paper but we plan to address it in our future work. Furthermore, our simulation input parameters are intended to resemble real data centers as closely as possible in terms of size and power, and provides clear guidelines for green data centers' designers.

Managing energy sources for green data centers. Researchers at University of Florida, IDEAL Lab, propose iSwitch [13], a novel dynamic load power tuning scheme for managing intermittent renewable energy sources. The study introduces a renewable energy utilization (REU) metric, defined as (PL / PR) x 100%, where PL is the amount of renewable power utilized by the load and PR is the total renewable power generation. Instead, we study another parameter called Minimal Percentage Supply (MPS) which is the percentage of total energy consumption that can be driven by available renewable energy, given as renewable energy divided by energy consumption converted in percentage.

Studies on battery usage in data centers have also been conducted by [23],[11], [22] to optimize the energy management and minimize the energy cost. This study does not include the usage battery as an energy storage, but initiates a discussion on the impact of energy storage to the cost model and how to integrate such a factor when modelling a data center.

III. Available renewable energy

In our study, we consider renewable energy produced by wind turbines and solar panels. To simulate the system and analyze the results, we must first model both the consumption and production rate of our datacenter and energy sources. Since the weather and the season directly influences the production of renewable energy, we must utilize a weather model to predict the production rate. We must also use a simulation environment realistic enough to accurately model the energy consumption of a datacenter.

For this we have chosen three geographically distributed locations for investigating the feasibility study of using renewable energy. Firstly we chose Turku, Finland at 60° latitude as our reference because of the increased interest in constructing datacenters in northern countries. Secondly we chose Crete, Greece at 35° latitude because of its typically solar intense southern European climate. And thirdly we selected, Ilorin, Nigeria at 8.5° latitude to cover the equatorial extreme point. For each of these locations we are going to analyze the generation of renewable energy using solar- and wind power. In this section we describe the total amount of renewable energy produced in one year for our chosen geographical location, and in Section V we compare the production of energy to the consumption.

Data collection We collected the weather data from different sources. The weather data for Finland was collected from a weather station located at Åbo Akademi University in Turku, Finland [3]. Sensors in this weather station [12] measure a variety of meteorological data, including wind speed and direction, temperature, humidity, barometric pressure, rain and solar radiation.

For the non-local geographical locations, we collected the solar radiation data from `http://solrad-net.gsfc.nasa.gov/`. The website contains freely available data from solar radiation such as various forms of radiation data and the energy intensity measured by pyranometers which are compatible with the weather data from the Finnish location. All data is sampled by at least the granularity of one hour. For describing the production rate of a solar panel, we acquire the data containing the solar power radiance on a horizontal 1 m^2 solar panel, and we calculated the produced power in Watts describe later in our power model. We acquired the local wind speed data from the same weather station in Turku [3], and from `https://mesonet.agron.iastate.edu/` for the non-local data. The wind speed data was converted to meter/seconds $[m/s]$ from the non-local weather data in order to match with the local weather data. All data is sampled by at least the granularity of one hour.

III.1 Solar power model

The solar power model is constructed by analyzing the solar radiation obtained from the weather data, and by considering the following trigonometrical aspects of the radiation angle and practical aspects of the solar panel:

- *Angle tilt:* The power incident on a solar panel depends not only on the power contained in the sunlight, but also on the angle between the module and the sun. Referring to [4], we calculate the optimal angle at which a solar array should be tilted in order to achieve maximum energy through the year. Different geographical locations with different latitude are operating optimally using different angle tilt with respect to the horizontal plane. In all cases we assumed that the angle tilt is fixed throughout the year for all geographical locations, but we assume that the solar array tracks the sun on the vertical axis (east to west). Equation 1 shows the power generation of a 1 m^2 solar panel as:

  $$P_{solar} = P_{solar\_h} \times sin(\alpha + \beta)/sin(\alpha) \qquad (1)$$

  where P_{solar_h} is the solar radiance in the horizontal plane we already have from weather data, α is the sun elevation angle through the year and β is the tilt angle of the module measured from horizontal plane, 45°. The value for α is calculated according to Equation 2:

  $$\alpha = 90 - \phi + \delta \qquad (2)$$

  where ϕ is the latitude (60°) and δ is the declination angle computed in Equation 3 as:

  $$\delta = 23.45^\circ \times sin[360 \times (284 + d)/365] \qquad (3)$$

  where d is the day of the year.

- *Solar panel efficiency:* is the percentage of the sunlight energy that is actually transformed into electricity because of limitations in the solar panel cells. Today's solar panel technology (multi-crystalline silicon) efficiency value varies from 15% up to 18% – which is the record of 2015 [19]. Therefore, we multiply all hourly solar energy values with the coefficient 0.18 in order to achieve realistic data.

- *Solar inverter efficiency:* is the efficiency of the inverter connected between the solar panel cells and the AC grid. According to [20], the average coefficient of the DC-AC power converting today is 95%. Thus, we take this value into account to assure accurate and realistic power values.

III.2 Wind power model

The wind power model describes the power generation from the wind turbines in the system. To produce the wind energy we have chosen a HY 1000 [21], 5 blade wind turbine generating a peak output power of 1200 W. We chose this model because of its availability on the market and because of its suitable size for our datacenter. The wind power model is constructed by taking into consideration the following key features:

- *Wind turbine power curve:* According to the power profile in the technical specifications, we constructed the mathematical model of power as a function of wind speed. Equation 4 describes the power production of a wind turbine as follows:

  $$P_{wind} = 1151 \times exp(-((wind_{speed} - 14.28)/6.103)^2) \tag{4}$$

  where $wind_{speed}$ is the wind speed in $[m/s]$. The parameters in Equation 4 were obtained by using curve fitting tools in Matlab.

- *Wind inverter efficiency:* according to [5], wind turbine power converters typically reach an efficiency of 95%. Thus, we multiply this value with the prediction of the power model to provide a more accurate and realistic model.

Finally, the total renewable power model is given as:

$$P_{renewable} = P_{solar} + P_{wind} \tag{5}$$

which is simply the sum of the total solar and total wind production. As a result of the above processing and calculations, we have available total renewable (solar and wind) energy information in hourly granularity for the whole year.

IV. Renewable Energy Analysis

To illustrate the impact of the weather conditions on the renewable energy production, we used the previously defined power models for the wind turbine and solar panels to calculate the total sum of the produced energy for each month of the year. The weather data was collected at the following points in time:

Finland: January 1, 2012 – December 31 2012
Greece: January 1, 2006 – December 31 2006
Nigeria: January 1, 2011 – December 31 2011

Even though the data origins from different years, we assume that the average over one year will provide a sufficiently accurate and comparable result. Figure 1 shows the energy production of a 1 m^2 solar panel in Finland, Greece and Nigeria Figure 2 shows the energy production of one 1200W wind turbine, and Figure 3 shows the total sum of both energy sources throughout one year in each location.

The very predictable weather in Ilorin, Nigeria shows an almost constant solar energy production in Figure 1. Since all days throughout the year is approximately 12h, there is only a slight difference between winter and summer months. The low point is in July due to weather conditions such as rainy seasons with an extensive cloud coverage. In Crete, Greece, the 35°latitude and solar intensity provides a large but varying energy production. The winter months in Greece provide far less sunlight than the summer months, and have therefore a lower energy production than Nigeria. However, the days in the summer months are longer, and the solar energy produced in one day exceeds the energy productions of Nigeria even if the intensity of the solar radiation is larger in Nigeria. The most varying results are measured in the Finnish location. The winter months produce almost no solar energy because of a very short time of sunlight during the day. On the other hand, during the summer the solar energy production can exceed both Greece and Nigeria; in this case during May and June because of the long duration of sunlight during the day. Table 1 finally shows the energy values in kWh for each of these extreme points for total, solar and wind energy.

Also the wind speed is relatively constant in Nigeria throughout the year as seen in Figure 2. The wind speed is relatively low in most months with the exception of a slight increase during August and September. The wind speed in Greece is, on the other hand, very strong in the early months

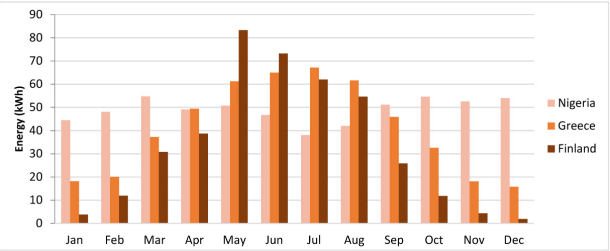

Figure 1: Solar energy produced by 1 m^2 solar panel in three geographical locations during one year

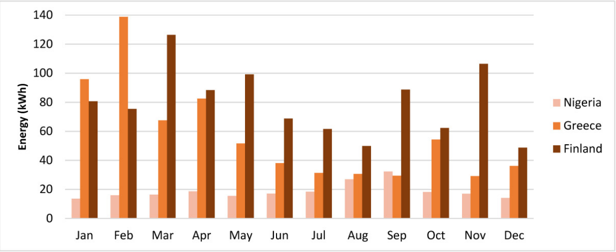

Figure 2: Wind energy produced by a 1200W wind turbine in three geographical locations during one year

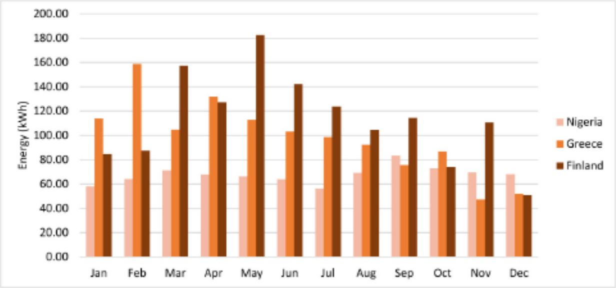

Figure 3: Combination of Solar- and wind energy produced in three geographical locations during one year

Table 1: Total renewable, solar- and wind energy (kWh) extreme months values, from 1 m^2 *solar panel and a 1200W wind turbine*

	Min month	Min energy	Max month	Max energy
Finland				
Solar	Dec.	1.89	May	83.34
Wind	Dec.	48.71	Mar.	126.36
Total	Dec.	50.6	May	182.52
Greece				
Solar	Dec.	15.75	Jul	67.12
Wind	Nov.	29.12	Feb.	138.80
Total	Nov.	47.21	Feb	158.83
Nigeria				
Solar	Jul.	37.98	Mar.	54.78
Wind	Jan.	18.90	Sep.	44.85
Total	Jul.	56.38	Sep	83.45

of the year, also seen in Figure 2, with a maximum in February. This high wind speed causes almost a possible 140 kWh of energy to be produced with the aforementioned wind turbine. It is about 7x higher than Nigeria and almost twice as high as the related wind production in Finland. During the summer month, the wind production in Greece is lower and hits the minimum about 4x lower than the wind production in February. The wind speed in Finland is typically more randomized, with a slight decrease during the summer months as seen in Figure 2. Overall though the year, the wind energy generation is highest in Finland compared to the other locations, even during summer months.

With this data, we will analyze the extreme months of maximum and minimum wind and solar energy as we intend to investigate the feasibility of using renewable energy sources during one year. Furthermore, the data used to build this model can be applied to other locations by considering different input values of latitude and weather characteristics for the selected area without modifying the core method. All data is freely available at: `https://doi.org/10.5281/zenodo.154401`

V. Energy consumption

To account for all the attributes included in causing energy consumption in a datacenter, we used an already made simulation environment,

System simulation We performed the simulations using the Philharmonic simulator developed by Vienna University of Technology, freely available at [15]. It is an open source cloud simulator used to calculate energy consumption and electricity costs for datacenters. The simulator allows the user to input configuration parameters such as the number of physical machines (PM), virtual machines (VM) and internal specification parameters such as clock speed, RAM size etc. Virtual Machines are virtual entities running over the physical machines and performing workload tasks. The cloud control algorithm decides on scheduling the workload using VM migrations and frequency scaling of the physical machines to control the power dissipation[3]. The workload is modelled with user requests uniformly distributed in time and duration[17]. Figure 4 illustrates the overview of the Philharmonic simulator. A given workload and cloud server settings are taken as input after which the tool simulates the scheduling of the workload on the defined server cloud.

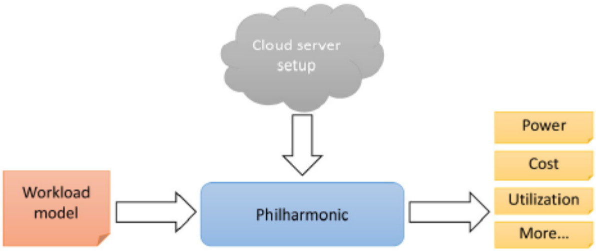

Figure 4: The Philharmonic simulator uses a cloud server setup and a defined workload to calculate power dissipation, cost, utilization and other parameters as a function of time

We used 3 different data center sizes to observe the proportion by which they impact energy consumption. The PMs are configures with 1-4 CPU cores and 16-32 GB RAM, to model a heterogeneous infrastructure. Each VM is configured to have one CPU core and 4-16 GB amount of RAM to vary resource utilization over time. The workload consists of user requests to be handled by VMs. The user requests are

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[3] The power model of the Philharmonic simulator was developed during a NESUS STSM at TU Wien May 2015 and is to appear in IEEE Transactions 2016

generated randomly by uniformly distributing the creation time and their duration. Each of the requests can either ask for a new VM to be booted or an existing one to be deleted. The specifications of the requested VMs were modelled by normally distributing each resource type, i.e 4-16 GB of RAM. Further details on the simulator can be found in [16] and [17].

The total duration of the simulation was set to 1 week, with 1 hour step size in order to be compatible with the energy production data. The simulation step size was selected based on the available weather data input of solar and wind energy, so that we can compare hourly available renewable and consumed energy. Finally, the cloud control algorithm decides on the suitable VM migrations and frequency scaling of the physical machines to make the scenario as realistic as possible. The best cost fit frequency scaling (BCFFS) cloud controller described in [17] was used.

Consumed energy We defined input scenarios of 500 to 2500 PMs in the Philharmonic simulator, with a step size of 1000 PMs. The number of virtual machines was chosen 2 fold the number of physical machines for each simulation in order to replicate a realistic scenario. We replicate results of one week for every week of the year, assuming that the workload weekly pattern is homogeneously distributed over the year. As a result, Table 2 shows the total energy consumption for 3 server scenarios during one week and one year.

Table 2: Weekly and annual energy consumption (kWh) of different data center configurations

Nr.	nr. PMs	nr. VMs	weekly energy	annual energy
1	500	1000	2425	126500
2	1500	3000	7285	380200
3	2500	5000	12146	634000

VI. Minimal Percentage Supply

With a model of both energy production (in Section III) and energy consumption (in Section V), we evaluate different scenarios to investigate the feasibility of using renewable energy sources in different geographical locations. We give the notion of a new metric *Minimal Percentage Supply* (MPS), used to determine the data center energy coverage provided from 1 single turbine and 1 m^2 solar panel. Furthermore, we build a quantity model describing the number of wind turbines and solar panels needed to obtain a certain energy coverage in a certain location. MPS is calculated as:

$$MPS = \frac{RenewableEnergyProduction(kWh)}{TotalEnergyConsumption(kWh)} \times 100\% \qquad (6)$$

Table 3: MPS annual, maximal and minimal months values in percentage

Scenario Nr.	1	2	3
Finland			
Annual MPS(%)	1.17	0.39	0.23
May MPS(%)	1.88	0.62	0.38
December MPS(%)	0.52	0.17	0.10
Greece			
Annual MPS(%)	1.01	0.34	0.20
May MPS(%)	1.16	0.39	0.23
December MPS(%)	0.54	0.18	0.11
Nigeria			
Annual MPS(%)	0.70	0.23	0.14
May MPS(%)	0.68	0.23	0.14
December MPS(%)	0.70	0.23	0.14

When comparing the energy production with the energy consumption, we determine the MPS value for each data center setting. Table 3 presents the annual, Maximum and Minimum MPS values when applying the respective energy values to Equation 6. The results from Table 3 indicate that the order of magnitude for powering such a datacenter is roughly between 10^2 and 10^3.

We further analyze Scenario 2 datacenter with different MPS values. The MPS of 100%, 75% and 50% for a datacenter of size according to Scenario 2 is illustrated in Figures 5 and 6. The figures illustrate the requirements in both solar and wind power, and various combinations for all three geographical locations. Figure 5 shows the results from May month, since it is the best case scenario for our reference location: Finland. As seen in Figure 5, the least amount of solar or wind power sources are required in Finland to meet the MPS constraints compared to Greece and Nigeria. For example, for an equal distribution of solar- and wind energy a MPS of 75% can be achieved in Finland, while the same configuration only provides 50% MPS in Greece. This is due to the long duration of sunlight in Finland during the summer months in combination with moderate wind production throughout the year.

Figure 6 shows the same MPS configurations as in Figure 5 but for the worst-case month in Finland: December. Since the duration of sunlight during the day is very limited, a very large amount of solar panels are needed to cover the MPS of the Scenario 2 datacenter. For MPS values over 75%, more than 10^4 m^2 of solar panels are needed, which is orders of magnitude more than both Nigeria and Greece. Combining solar power with wind power decreases the number of

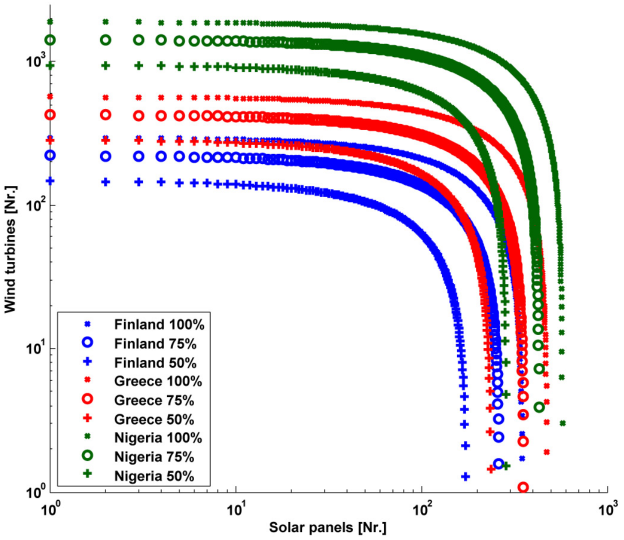

Figure 5: MPS of 100%, 75% and 50% for three geographical locations in May month

required panels, and half an order of magnitude is decreased for a 50/50 configuration. However, with the limited amount of sunlight in December, Finland is only competitive with Greece and Nigeria when using a significantly larger amount of wind turbines.

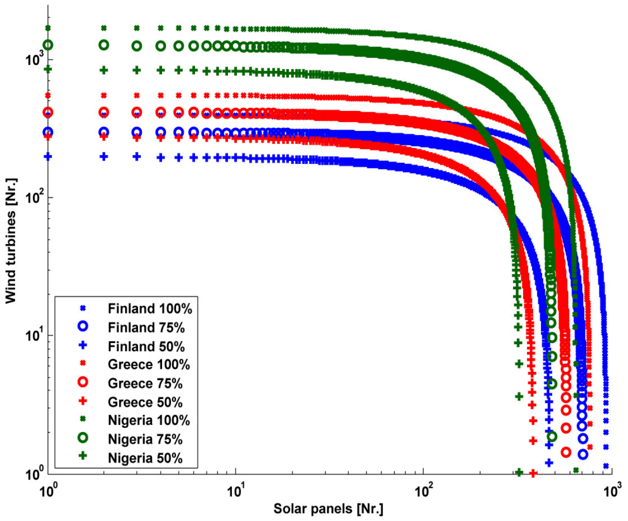

Figure 6: MPS of 100%, 75% and 50% for three geographical locations annually

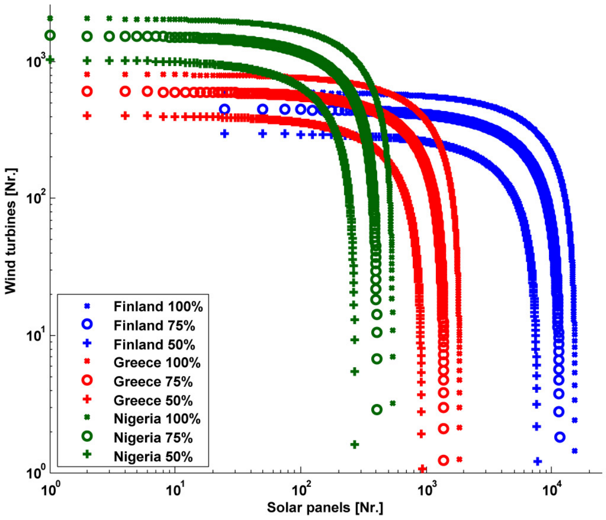

Figure 7: MPS of 100%, 75% and 50% for three geographical locations in December month

Figure 7 finally shows the MPS for the annual average energy productions from solar- and wind power. Similarly to the previous figures, the MPS values for 100%, 75% and 50% coverage is shown for all three geographical locations. On an annual average all three locations have the same order of magnitude in energy production, but a few details differ. With the predictable and high intensity sunlight in Nigeria, the annual average energy production from solar power is higher than the wind power. Greece has a more balanced annual energy generation from solar- and wind power. For example using 150 solar panels and 450 wind turbines reaches 100% MPS in Greece while the same configuration in Nigeria results in only 50% MPS. Lastly, Figure 7 shows that Finland reaches the MPS coverage faster than the other locations on an annual basis only if the ratio solar-to-wind is about 1:2.

As seen in the table, there is a 3 fold difference between minimal and maximal MPS values, which clearly indicates different operational costs for producing the same amount of renewable energy during different times of the year. Obviously, we need more physical resources, i.e wind turbines and solar panels, in December to produce same amount of energy compared to May.

VII. CONCLUSIONS

In this paper we analyzed the feasibility on competitiveness of powering datacenters with renewable energy at 60°latitude. The energy production on different geographical locations was determined by an energy model based on real weather data from three geographical different locations, and the energy consumption of different datacenters was simulated on a hourly basis for one year. In order to measure the renewable coverage over the energy consumption of a datacenter a new metric is introduced, called Minimal Percentage Supply (MPS). We built a model for relating the quantity between solar- and wind energy sources in order to achieve a certain MPS coverage with renewables.

Results indicate that the geographical location influences heavily the utilization of renewable energy; for northern latitudes, energy produced from only solar energy is feasible during the summer months, but probably insufficient during the winter months because of the low amount of sunlight during the day. To achieve competitive MPS on a 60°northern latitude on an annual basis, the ratio of solar-to-wind energy must be about 1:2. However during the summer months, competitive (or higher) MPS is achieved on 60 °latitude location independent of the solar-to-wind ratio and using 30-40% less energy generators. During the winter months in Finland, the lack of sunlight naturally deems solar power highly inefficient, and a competitive MPS value is only achieved with a solar-to-wind ratio of roughly 1:1.5. Also, during the winter months in Finland 1.3x the amount power generators must be installed in order to reach the same power generation as the summer months in Finland.

Using this information datacenter designers can determine the feasibility and cost efficiency of constructing data centers powered by renewable energy on a northern latitude.

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