Detailed Write Up for Global Power Plant Database

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Global Power Plant Database:

Introduction:

Electricity has become an essential part of everyday human life since its invention. All things around us are powered by electricity. But where does this come from? Obviously from the power plants that generate them. These power plants all have different capacities, different fuel types, are in different places and produce different amounts of electricity.

The data taken for this report is from (Byers 2021). It has various statistics from power plants around the world and really gives us insights on different fuel types, location, energy generated, capacity and much more about them.

Different countries have different demands for electricity in different sectors, biggest of them is domestic use, industrial use and many more as seen in pie chart in (Administration, US Energy Information 2023) . It makes sense that countries with the highest population will have higher consumption and therefore highest production of electricity. This includes top 10 most populated countries like China, India, USA, Indonesia, Pakistan, Nigeria, Brazil, Bangladesh, Russia, and Mexico mentioned in (O'Neil 2023).

This data is slightly different when we look into the top energy producers are China, USA, India, Russa, Japan, Brazil, Canada, South Korea, Germany, and France according to (Department, Statista Research 2023). We can also see neat graph provided in (Fernández 2023) to get a good idea of energy consumption and production.

To satisfy this massive demand there needs to be various fuel sources but which one of those fuel sources keeps up with it. This may be different country wise as different countries have different natural resources available for production of electricty. Maybe countries which are abundant in natural resources like Oil and Gas to produce electricity. These countries include gulf countries like Saudi Arabia, Iraq, Kuwait, Qatar and many others. Also others which are not in the region like Azerbaijan, Venezuela, Libya, Nigeria etc (Brown 2023). These countries' GDP is supported by exports of these abundant fuels and in most cases economies are dependent on them (Workman 2023).

What about other countries which don't have Oil or Gas. What do they rely on? These countries have to tackle these problems in creative ways like using Nuclear, Wave, Wind, Solar, Hydro energy. Some of the leaders in this space are Sweden whose 50% energy produced was renewable in 2012, Costa Rica with 98% of its electricity from renewable sources, UK being leader in wind energy powering 7.5 million households, and many more (Climate Council 2022).

Even countries that are not on the list have set targets towards use of more renewable resources. Recent push by the United Nations to combat climate change and promote renewable energy has many benefits. The United Nations mentions it is cheaper, healthier, creates jobs, and makes financial sense (United Nations 2023). There are many creative ways to tackle this like never turning turbines, solar canals, solar powered windows etc (Agenda 2023). Many countries have also promised to switch to a high percentage like 110 countries coming together to sign the COP28 deal to triple renewable electricity production by the year 2030 (Kumari 2023). This program was held in Dubai in 2023. Also countries have set individual goals to combat this like India setting goal to reach net zero carbon emissions by 2070 and to fulfil 50% electricity required through renewable sources till 2030 (Birol and Amitabh Kant 2022), China being 5 years ahead of their doubling of solar and wind power capacity (Jones 2023), USA targeting to remove electricity produced by fossil fuels by 80% by 2030 and being 100% carbon neutral after 5 more years (Mai 2023), and many more.

But many countries have failed in the past to achieve this target as an article by the United Nations says: “Despite evidence that renewables are the most affordable energy source to both improve resilience and support decarbonisation, governments across the world continue to resort to fossil fuel subsidies to keep energy bills under control. This growing gap between countries’ ambition and action on the ground is alarming and sends a clear warning that the global energy transition is not happening.” (United Nations 2022). We will dig into our data and see sources of energy used by different countries, their efficiency compared to other sources, their actual utilisation and plants using different sources.

Method:

The “Global Power Plant Database” contains information regarding 35,000 power plants which are located in 167 different countries. It includes plants involving all types of fuels for example oil, gas, nuclear, coal, waste, biomass, geothermal, hydro, wind, wave, and solar. It has in total 36 columns:

No.	Column Name	Column Description
1	country	3-character country code according to ISO 3166-1 alpha-3 specification

2	country_long	Name of the country
3	name	Name of the power plant
4	gppd_idnr	10 or 12 character identifier for the power plant
5	capacity_mw	Electricity generating capacity in MGW (Megawatts)
6	latitude	Geolocation in decimal degrees
7	longitude	Geolocation in decimal degrees
8	primary_fuel	Primary energy source of power plant
9	other_fuel1	Other energy source of power plant
10	other_fuel2	Other energy source of power plant
11	other_fuel3	Other energy source of power plant
12	commisioning_year	Year of plant operation
13	owner	Majority shareholder of the power plant
14	source	Organisation reporting the data
15	url	Source link
16	geolocation_source	Source for geolocation of power plant
17	weep_id	Unique plant identifier used in PLATTS-WEPP database
18	year_of_capacity_data	Year of the capacity being reported
19	generation_gwh_2013	Reported electricity generated in gigawatt-hours (2013)

20	generation_gwh_2014	Reported electricity generated in gigawatt-hours (2014)
21	generation_gwh_2015	Reported electricity generated in gigawatt-hours (2015)
22	generation_gwh_2016	Reported electricity generated in gigawatt-hours (2016)
23	generation_gwh_2017	Reported electricity generated in gigawatt-hours (2017)
24	generation_gwh_2018	Reported electricity generated in gigawatt-hours (2018)
25	generation_gwh_2019	Reported electricity generated in gigawatt-hours (2019)
26	generation_data_source	Data source that reported the generation in gigawatt-hours
27	estimated_generation_gwh_2013	Estimated electricity generated in gigawatt-hours (2013)
28	estimated_generation_gwh_2014	Estimated electricity generated in gigawatt-hours (2014)
29	estimated_generation_gwh_2015	Estimated electricity generated in gigawatt-hours (2015)
30	estimated_generation_gwh_2016	Estimated electricity generated in gigawatt-hours (2016)
31	estimated_generation_gwh_2017	Estimated electricity generated in gigawatt-hours (2017)
32	estimated_generation_note_2013	Model used to estimate electricity generated in gigawatt-hours (2013)
33	estimated_generation_note_2014	Model used to estimate electricity generated in gigawatt-hours (2014)

34	estimated_generation_note_2015	Model used to estimate electricity generated in gigawatt-hours (2015)
35	estimated_generation_note_2016	Model used to estimate electricity generated in gigawatt-hours (2016)
36	estimated_generation_note_2017	Model used to estimate electricity generated in gigawatt-hours (2017)

So, we have all the data available to explore our introduction. We load this dataset in R for our analysis:

```
csv_file <- "test/global_power_plant_database.csv"
dataset <- read.csv(csv_file)
```

First I checked if top population countries actually had the most electricity produced given their possibly massive demand. But for a line graph a column needed to be selected that indicated that country's production, we directly don't have that column but we can add columns generation_gwh_2013, generation_gwh_2014, generation_gwh_2015, generation_gwh_2016, generation_gwh_2017, generation_gwh_2018, and generation_gwh_2019 for that. Looking at the data one can see that most of the entries in those columns are empty and not reported by the power plants or the data sources from which the other information about the plant has been collected.

So if we move forward with these columns , results won't be much reliable. So instead I choose columns which have data in them (estimated_generation_gwh_2013, estimated_generation_gwh_2014, estimated_generation_gwh_2015, estimated_generation_gwh_2016, estimated_generation_gwh_2017). Even though estimates this will give us a general idea of top countries. Line graph was made for top 100 countries and summing up estimated_generation_gwh columns for particular year for that countries using R code:

```r
# Load the ggplot2 package
library(ggplot2)

# Filter top 10 countries
selected_countries <- c("China", "United States of America", "Canada",
"Brazil", "India", "Russia", "Norway", "Japan", "Venezuela", "Spain")
selected_data <- dataset[complete.cases(dataset[, c("country_long",
"estimated_generation_gwh_2013", "estimated_generation_gwh_2014",
"estimated_generation_gwh_2015", "estimated_generation_gwh_2016",
"estimated_generation_gwh_2017")]), ]
selected_data <- selected_data[selected_data$country_long %in%
selected_countries, ]

# Sum up the total energy produced for each year and country
total_energy <- selected_data %>%
  group_by(country_long) %>%
  summarise(
    energy_2013 = sum(estimated_generation_gwh_2013),
    energy_2014 = sum(estimated_generation_gwh_2014),
    energy_2015 = sum(estimated_generation_gwh_2015),
    energy_2016 = sum(estimated_generation_gwh_2016),
    energy_2017 = sum(estimated_generation_gwh_2017)
  )

# Reshape the data for plotting
total_energy_long <- tidyr::gather(total_energy, key = "year", value =
"energy", -country_long)

# Create a line chart for total energy produced in selected countries
ggplot(total_energy_long, aes(x = year, y = energy, group = country_long,
color = country_long)) +
  geom_line() +
  geom_point() +
  labs(title = "Total Energy Produced in top 10 Countries (2013-2017)",
       x = "Year",
       y = "Total Energy Produced (GWh)") +
  scale_x_discrete(labels = c("2013", "2014", "2015", "2016", "2017")) +
  theme_minimal()
```

But because this doesn't tell full story a line graph was created for estimated fuel totals of the year from 2013 to 2017 for all fuel sources using following R code:

```r
# Load the ggplot2 package
library(ggplot2)

# Filter rows with non-empty entries in the specified columns
selected_data <- dataset[complete.cases(dataset[, c("primary_fuel",
"estimated_generation_gwh_2013", "estimated_generation_gwh_2014",
"estimated_generation_gwh_2015", "estimated_generation_gwh_2016",
"estimated_generation_gwh_2017")]), ]

# Sum up the total energy produced for each year and fuel type
total_energy <- selected_data %>%
  group_by(primary_fuel) %>%
  summarise(
    energy_2013 = sum(estimated_generation_gwh_2013),
    energy_2014 = sum(estimated_generation_gwh_2014),
    energy_2015 = sum(estimated_generation_gwh_2015),
    energy_2016 = sum(estimated_generation_gwh_2016),
    energy_2017 = sum(estimated_generation_gwh_2017)
  )

# Reshape the data for plotting
total_energy_long <- tidyr::gather(total_energy, key = "year", value =
"energy", -primary_fuel)

# Create a line chart for total energy produced by each fuel type
ggplot(total_energy_long, aes(x = year, y = energy, group = primary_fuel,
color = primary_fuel)) +
  geom_line() +
  geom_point() +
  labs(title = "Total Energy Produced by Fuel Type (2013-2017)",
       x = "Year",
       y = "Total Energy Produced (GWh)") +
  scale_x_discrete(labels = c("2013", "2014", "2015", "2016", "2017")) +
  theme_minimal() +
  theme(legend.position = "top", legend.title = element_blank())
```

But because this data only showed Hydro, Solar, and Wind (as most estimated and generated columns for fuels are actually empty), we went with sum of capacity_mw column for bar graph of all fuels. We excluded Other from this graph because it was already too crammed in X labels and removed empty cells if any:

```
# Load the ggplot2 package
library(ggplot2)

# Filter rows with non-empty entries in the specified columns
selected_data <- dataset[complete.cases(dataset[, c("primary_fuel",
"capacity_mw")]), ]

# Exclude "Other" as a fuel type
selected_data <- selected_data[selected_data$primary_fuel != "Other", ]

# Sum up the total capacity for each fuel type
total_capacity <- selected_data %>%
  group_by(primary_fuel) %>%
  summarise(total_capacity = sum(capacity_mw))

# Create a bar graph for total capacity by fuel type
ggplot(total_capacity, aes(x = reorder(primary_fuel, -total_capacity), y =
total_capacity, fill = primary_fuel)) +
  geom_bar(stat = "identity") +
  labs(title = "Total Capacity by Fuel Type",
       x = "Primary Fuel",
       y = "Total Capacity (MW)") +
  theme_minimal() +
  theme(axis.text.x = element_text(angle = 45, hjust = 1), legend.position =
"none")
```

After that we checked the top 25 countries for estimated generated electricity from 2013 to 2017 to see how fuels for which the data is available compare using a horizontal stacked bar chart:

```r
# Load the ggplot2 package
library(ggplot2)

# Filter rows with non-empty entries in the specified columns
filtered_data <- dataset[complete.cases(dataset[, c("country_long",
"primary_fuel", "estimated_generation_gwh_2013",
"estimated_generation_gwh_2014", "estimated_generation_gwh_2015",
"estimated_generation_gwh_2016", "estimated_generation_gwh_2017")]), ]

# Combine estimated generation for all years
filtered_data$total_generation <- rowSums(filtered_data[,
c("estimated_generation_gwh_2013", "estimated_generation_gwh_2014",
"estimated_generation_gwh_2015", "estimated_generation_gwh_2016",
"estimated_generation_gwh_2017")])

# Get the top 25 countries
top_countries <- names(sort(tapply(filtered_data$total_generation,
filtered_data$country_long, sum), decreasing = TRUE)[1:25])

# Filter data for the top 25 countries
top_countries_data <- subset(filtered_data, country_long %in% top_countries)

# Create a horizontal stacked bar graph for the top 25 countries
ggplot(top_countries_data, aes(x = total_generation, y = reorder(country_long,
-total_generation), fill = primary_fuel)) +
  geom_bar(stat = "identity") +
  labs(title = "Contribution of Fuels to Total Energy Produced",
       x = "Total Energy Produced (GWh)",
       y = "Country",
       fill = "Fuel Type") +
  theme_minimal() +
  theme(panel.grid.major = element_blank(),
        panel.grid.minor = element_blank(),
        panel.border = element_blank(),
        axis.line = element_blank())
```

Now to calculate the number of plants for each type and most commonly used secondary fuel we used this code:

```r
# Count of all fuel types in primary_fuel
primary_fuel_counts <- table(dataset$primary_fuel)
primary_fuel_counts_sorted <- primary_fuel_counts[order(-primary_fuel_counts)]
cat("Count of all fuel types in primary_fuel:\n")
print(primary_fuel_counts_sorted)

# Count of all fuel types in other_fuel1
other_fuel1_counts <- table(dataset$other_fuel1[dataset$other_fuel1 != ""])
other_fuel1_counts_sorted <- other_fuel1_counts[order(-other_fuel1_counts)]
cat("Count of all fuel types in other_fuel1:\n")
print(other_fuel1_counts_sorted)
```

We used the order function to order the results and excluded empty cells. Also, to calculate number of plants using other_fuel1 as Oil when primary_fuel is Gas and vice vera we used this code just by replacing "Gas" in first line with "Oil":

```r
# Filter dataset for entries where other_fuel1 is gas or oil
filtered_data <- dataset[dataset$other_fuel1 %in% c("Gas") &
!is.na(dataset$other_fuel1), ]

# Create a table
primary_fuel_table <- table(filtered_data$primary_fuel)

# Sort the table
primary_fuel_table_sorted <- primary_fuel_table[order(-primary_fuel_table)]

# Display the table
cat("Table of counts for unique primary_fuel values when other_fuel1 is gas or
oil (sorted in descending order):\n")
print(primary_fuel_table_sorted)
```

To dig little further we then created graph of top 25 countries with sum of capacity_mw column rather than estimates using this code similar to Figure 4:

```
library(ggplot2)

# Filter rows with non-empty entries in the specified columns
filtered_data <- dataset[complete.cases(dataset[, c("country_long",
"primary_fuel", "capacity_mw")]), ]

# Combine total capacity
filtered_data$total_capacity <- tapply(filtered_data$capacity_mw,
filtered_data$country_long, sum)[filtered_data$country_long]

# Get the top 25 countries
top_countries <- names(sort(tapply(filtered_data$total_capacity,
filtered_data$country_long, sum), decreasing = TRUE)[1:25])

# Filter data for the top 25 countries
top_countries_data <- subset(filtered_data, country_long %in% top_countries)

# colors
custom_palette <- c("#1f78b4", "#33a02c", "#e31a1c", "#ff7f00", "#6a3d9a",
"#a6cee3", "#b2df8a", "#fb9a99", "#fdbf6f", "#cab2d6",
                    "#b15928", "#01665e", "#d7191c", "#fdae61", "#fee08b",
"#d73027", "#4575b4", "#91bfdb", "#313695", "#fee08b",
                    "#d73027", "#4575b4", "#91bfdb", "#313695")

# Create a horizontal stacked bar graph
ggplot(top_countries_data, aes(x = total_capacity, y = reorder(country_long, -
total_capacity), fill = primary_fuel)) +
  geom_bar(stat = "identity") +
  scale_fill_manual(values =
custom_palette[1:length(unique(top_countries_data$primary_fuel))]) +  # Set
the custom color palette
  labs(title = "Contribution of Fuels to Total Capacity",
       x = "Total Capacity (MW)",
       y = "Country",
       fill = "Fuel Type") +
  theme_minimal() +
  theme(panel.grid.major = element_blank(),
        panel.grid.minor = element_blank(),
        panel.border = element_blank(),
        axis.line = element_blank())
```

Here I used some contrasting colors to see the different sections of graph clearly. To see efficiency of each fuel type I decided to conduct an independent ANOVA between primary_fuel and capacity_mw columns. To check assumptions:

1. Outliers:

```
# loading library for data functions
library(rstatix)

# grouping on primary_fuel column
fuel_grouping <- group_by(dataset, primary_fuel)


# Identify outliers for the 'capacity_mw' variable
outliers <- identify_outliers(fuel_grouping %>% select(primary_fuel,
capacity_mw), capacity_mw)

# Remove outliers from 'fuel_grouping'
fuel_grouping_no_outliers <- fuel_grouping %>%
  filter(!(primary_fuel %in% outliers$primary_fuel & capacity_mw %in%
outliers$capacity_mw))

outliers
```

I created grouping by primary_fuel variable so our original data isn't affected. Then I found 3616 outliers and removed them from the grouping.

2. Normality:

I conducted a Shapiro test on data, but it failed, giving error that "Sample size should be between 3 and 5000" for Solar fuel. So, I decided to create Histograms for each primary fuel and none of them looked normal, most of them were chi-squared so I dropped the idea of independent ANOVA. Here is code for the process:

```r
normality_test <- fuel_grouping_no_outliers %>%
  filter(!is.na(capacity_mw)) %>%  # Ignore empty cells
  group_by(primary_fuel) %>%
  summarise(shapiro_p_value = shapiro.test(capacity_mw)$p.value)

# View the results
print(normality_test)

 #Create a list of the unique primary fuel groups
fuel_groups <- unique(dataset$primary_fuel)

# Create a for loop for all histograms
for (fuel in fuel_groups) {
  fuel_grouping <- dataset %>% filter(primary_fuel == fuel)
  histograms <- fuel_grouping %>%
    ggplot(aes(x = capacity_mw)) +
    geom_histogram(binwidth = 1, position = "dodge", alpha = 0.7) +
    labs(title = paste("Distribution of capacity_mw for", fuel),
         x = "Capacity (MW)",
         y = "Frequency") +
    theme_minimal()
  print(histograms)
}
```

So now to understand the efficiency of a fuel I needed a different approach. I created a radial column chart in which I took by taking mean capacity of the fuel type for all fuels:

```r
library(ggplot2)

# Filter rows with non-empty entries
filtered_data <- dataset[complete.cases(dataset[, c("primary_fuel",
"capacity_mw")]), ]

# Calculate the average capacity for each primary_fuel
average_capacity <- filtered_data %>%
  group_by(primary_fuel) %>%
  summarise(average_capacity = mean(capacity_mw))

# Create a radial column chart
ggplot(average_capacity, aes(x = primary_fuel, y = average_capacity, fill =
primary_fuel)) +
  geom_bar(stat = "identity", position = "identity", width = 0.5) +
  coord_polar(theta = "y") +  # Radial transformation
  labs(title = "Average Capacity by Primary Fuel",
       x = NULL,
       y = NULL) +
  theme_minimal() +
  theme(axis.text.x = element_blank(),  # Hide x-axis labels
        axis.title.x = element_blank(),  # Hide x-axis title
        panel.grid = element_blank(),  # Remove gridlines
        axis.text.y = element_blank(),
        plot.title = element_text(hjust = 0.5))
```

This cleared up a lot of things going on between primary_fuel and capacity_mw.

Results:

The population of a country doesn't dictate the amount of energy produced by the country. By this logic top 10 electricity producers should be China, India, United States, Indonesia, Pakistan, Nigeria, Brazil, Bangladesh, Russia and Mexico respectively as mentioned in (O'Neil 2023)**.** But population is just one of the variables when it comes to this metric, there is some truth to it as we can see top 10 countries in electricity production through 2013 to 2017 and we do have India, China, and USA in the list. One thing to note here is that these are estimated values from models.

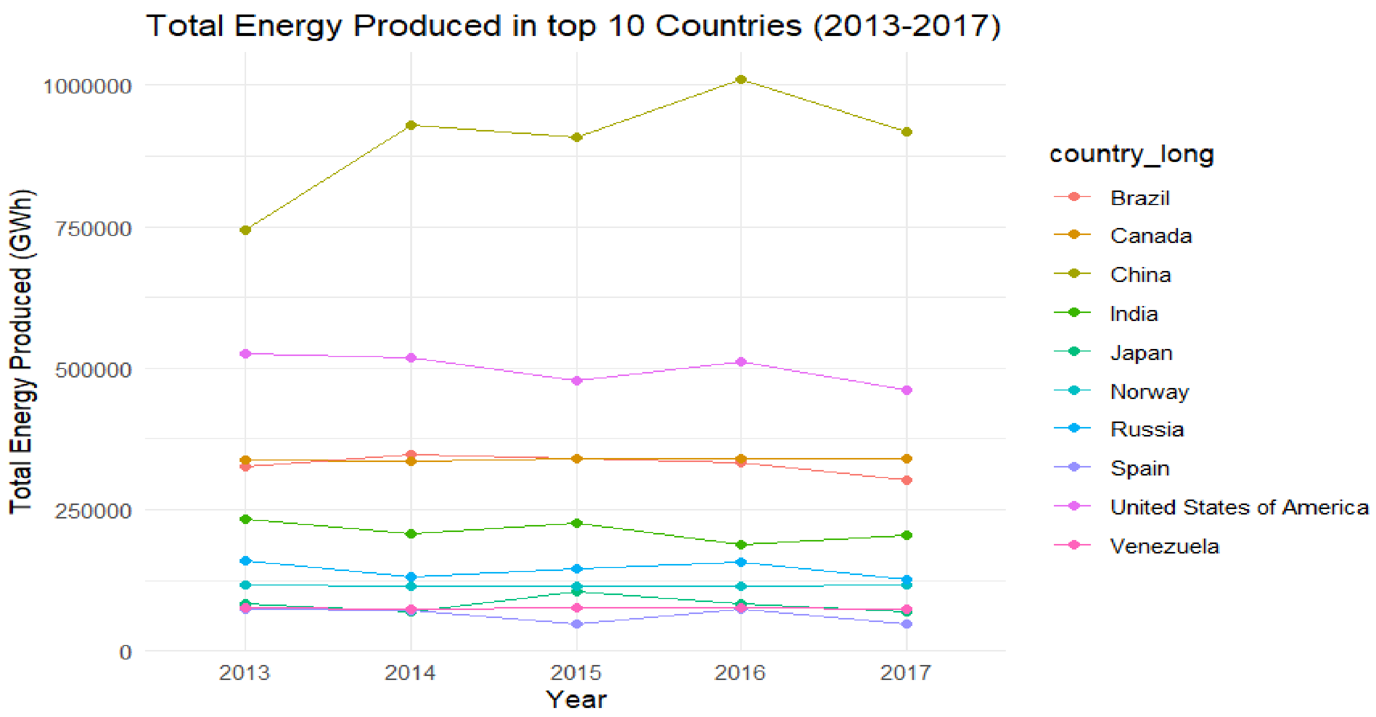


Figure-1

But this doesn't tell us the full story, this data is just differently available depending upon country's government, what sources they want to show and many other factors. Maybe variables like number of industries, factories, availability of electricity to population and others also play a role.

Now we see what top fuels are producing energy in the world:

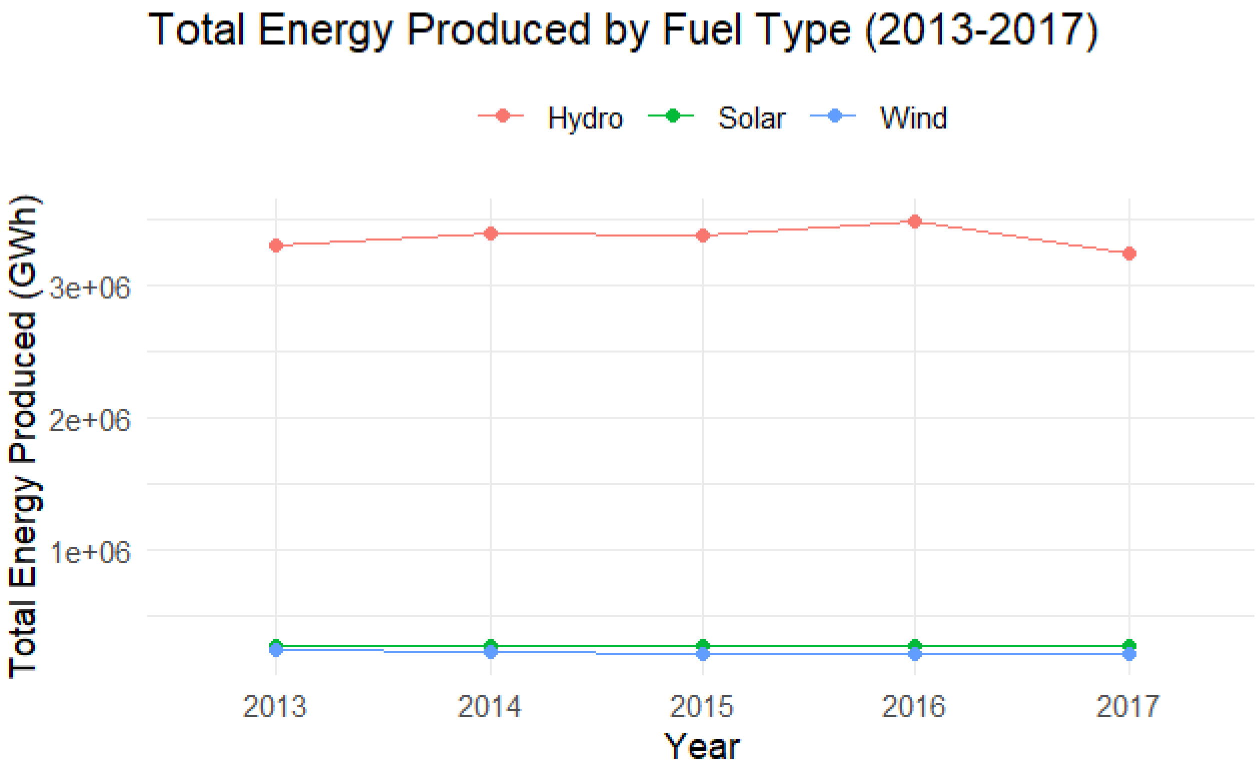


Figure-2

This doesn't seem right. Well, it turns out this data has mostly empty cells for fuel types other than Hydro, Solar, Wind which includes Oil, Gas, Coal, Biomass, Waste, Wave, Pet Coke, Geothermal, Cogeneration, Nuclear, and Storage in energy generated from 2013 to 2017. But why don't we have this data? Maybe because these types of plant don't report their actual data and thus there isn't any estimation model for it that the author could use.

Because of this limitation we must work around this limitation to find out answers.

Maybe we can see a more accurate graph through capacity and primary fuel types.

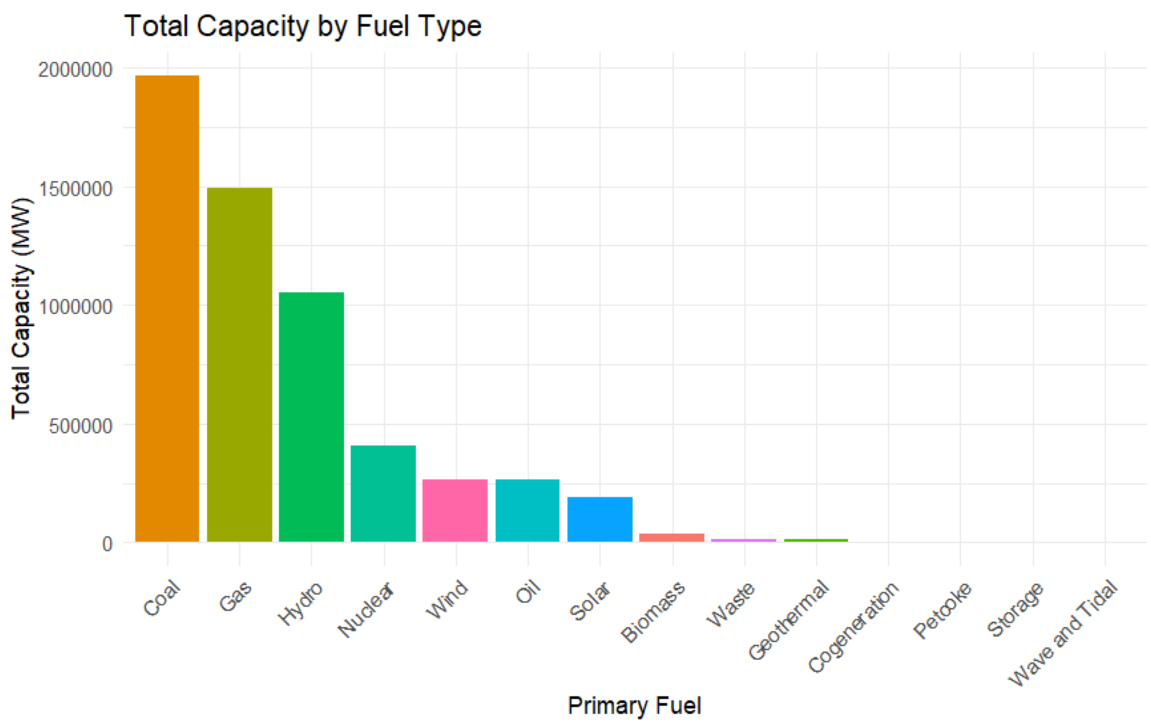
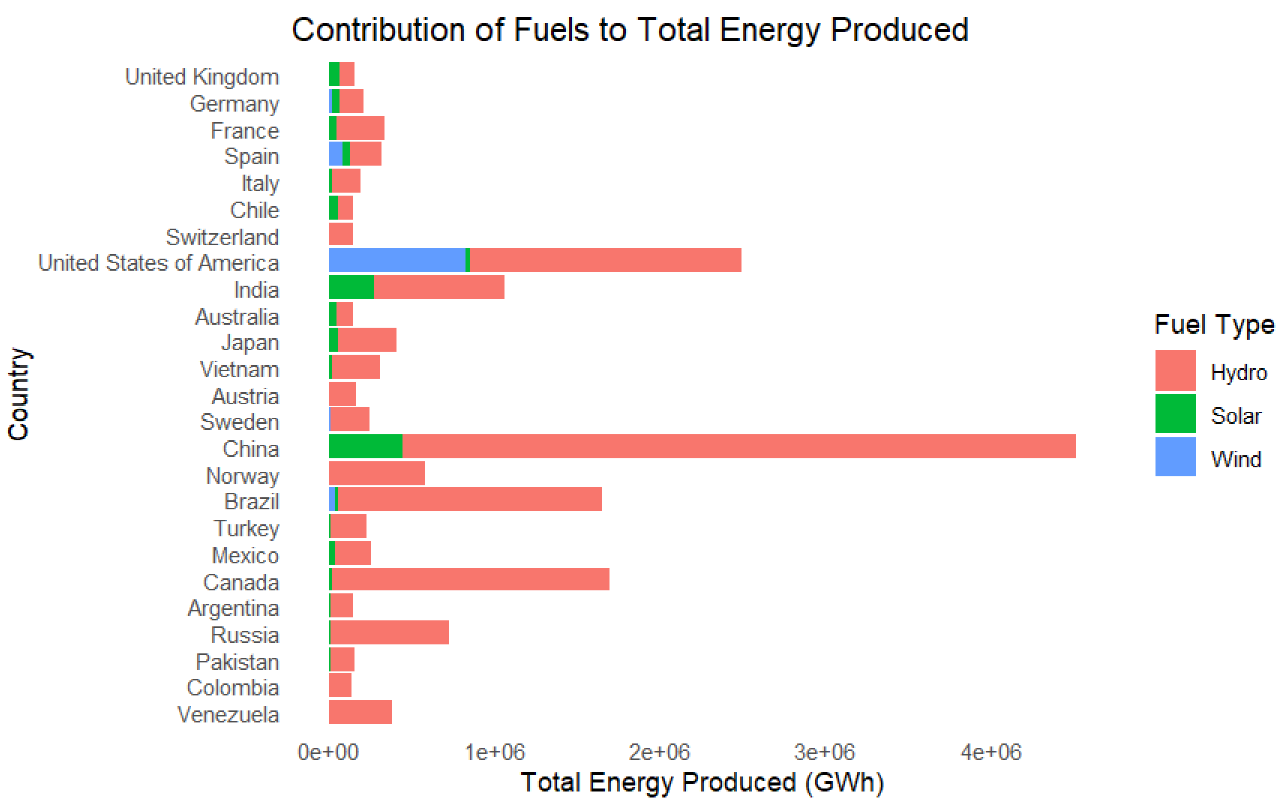


Figure-3

This definitely shows the bigger picture. There might be a reason that energy production data is available for only certain renewable sources of energy while big sources which produce most of the electricity and pollution are hidden behind. We can clearly see in the graph how big of a potential Coal and Gas have. It may be that revealing data for non-renewable sources is a bit controversial if it exceeds renewable sources. This could spark a backlash globally for the country and the company. Maybe we can dig a little deeper and get a graph of the number of factories for each fuel type in Figure-4.



Here we can again see that due to limitation of our data, we only get total electricity produced by only 3 fuels. Hydro is the most prominent among the 3. Maybe we can see something from the number of plants for each fuel type and compare it to Figure 3:

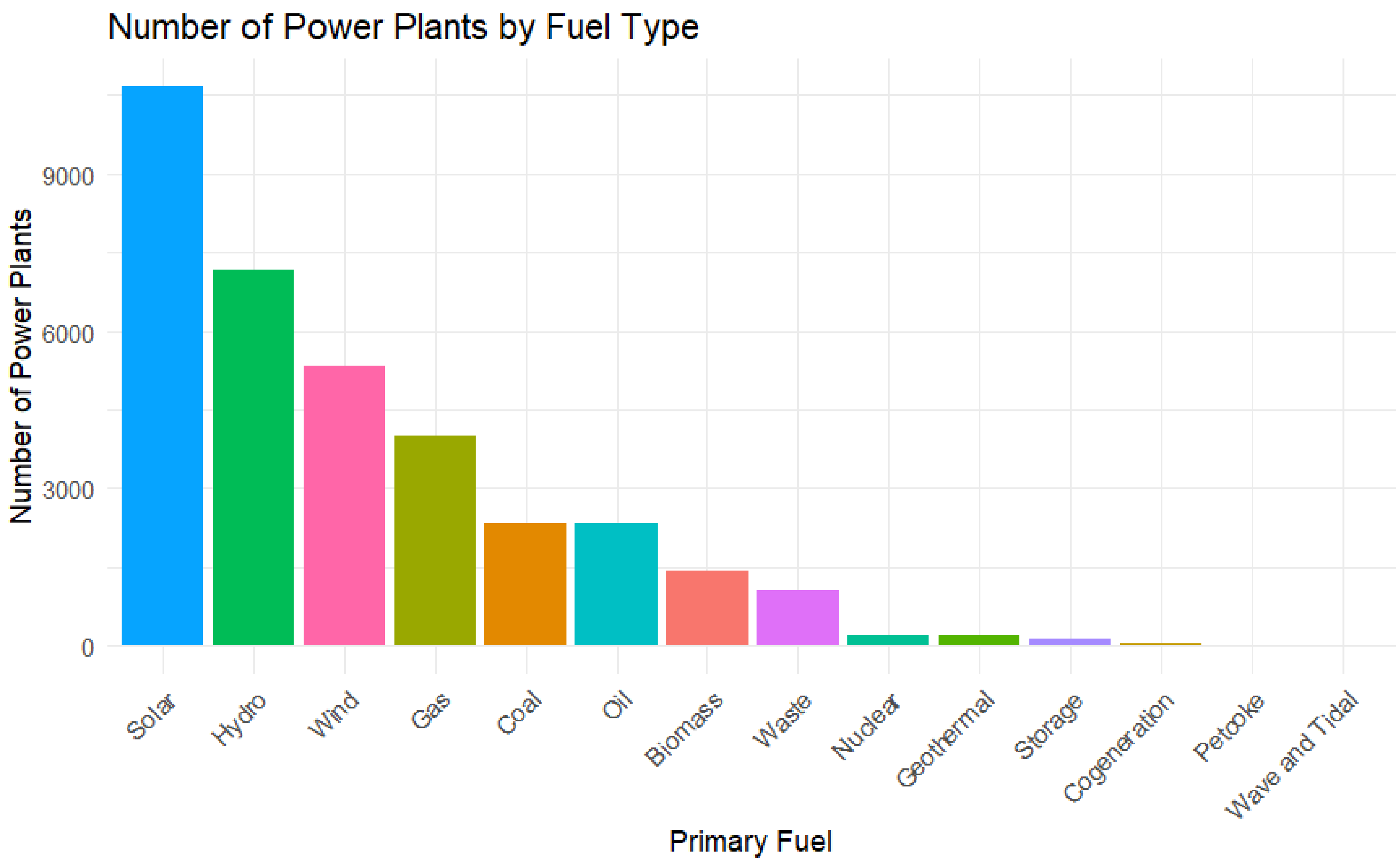


Figure-5

Here wind and Hydro make sense as seen in Figure 3 and 4 that they are a huge deal both in total theoretical capacity and contribution. Interesting how coal has the theoretical highest energy produced while Solar has highest number of plants. This can mean that Coal and Gas plants can produce more electricity than Solar, Hydro, and Wind. Whether they do or not is beyond the scope of data. Maybe solar energy plants don't produce much because they also rely on weather conditions for their production.

As we only have energy produced by data from Hydro, Solar and Wind let's move little forwards with that. Among them hydroelectricity is the top fuel producer in 126 countries, Solar in 90 and Wind in 26 from the available data. But we do find that most of the secondary fuel type in power plants is still Oil and Gas. 1169 and 383 plants still use Oil and Gas as secondary fuel source respectively. Now we don't have data that separates energy produced by each fuel in plants that have multiple fuel types. But we can confirm that power plants which have primary fuel such as Oil most commonly have secondary fuel source as Gas (795 Plants). Similarly, when primary fuel is Gas, secondary fuel is most commonly Oil (166 Plants). Here in Figure 6, a stacked bar graph showing the top 25 countries and their main fuels but ordered by capacity rather than estimated total produced so we can account for other fuel types.

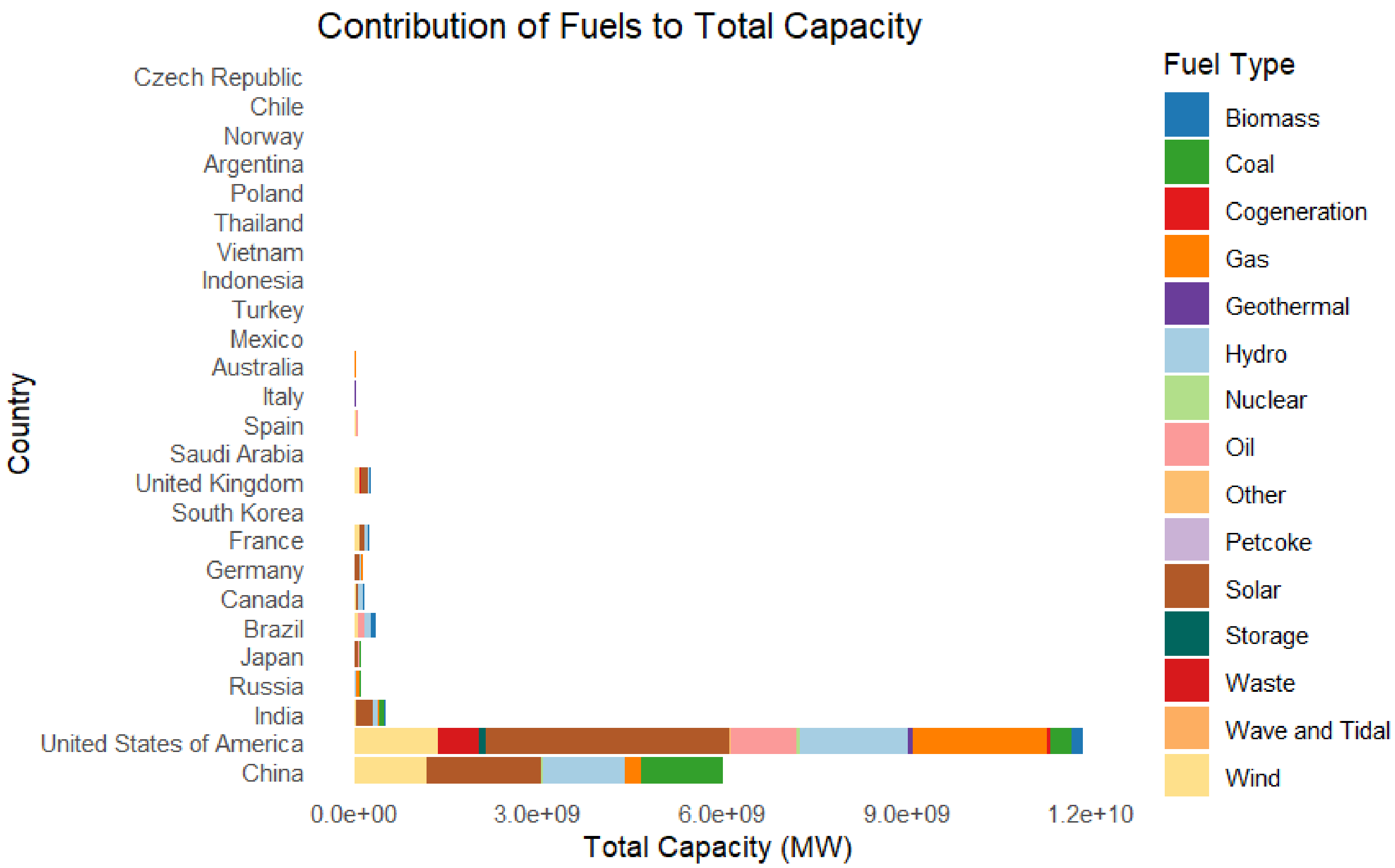


Figure-6

We can see that this tells a different story than when plotted against estimates of given data. Even many countries in the top 25 have changed. USA has more theoretical capacity than but from estimated values China produces more renewable energy. This doesn't provide enough evidence about other smaller energy producing countries but gives a general idea of what will be potential of this data if available correctly.

Notable things to see here are how top countries change, how high is the capacity difference and how untapped the potential of solar energy is. But if this is the case how efficient are these fuels are? We tried to conduct an independent ANOVA between capacity_mw and primary_fuel but assumptions weren't met. There were 3616 outliers which were removed to perform normality test but even that failed for all categories, so we have to take a different approach.

So, we can see many fuels have huge potentials but do these fuels have enough number of plants to capitalize on this potential:

It pretty much matches with the Figure 4:

Fuel Type	Number of Plants
Solar	10665
Hydro	5344
Wind	5344
Gas	3998
Coal	2330
Oil	2320
Biomass	1430
Waste	1068
Nuclear	195
Geothermal	189
Storage	135
Other	43
Cogeneration	41
Pet coke	12
Wave and Tidal	10

Even though there are these many numbers of plants solar energy falls short again, hydro and wind plant numbers do make sense. But concerningly Coal, Gas, and Oil also have a high number of plants. Maybe the number of plants and theoretical capacity differently tells a vague story. But even when I decided to combine them the statistical test couldn't be relied on. Let's see graph for efficiency of these fuels though their average maximum capacity:

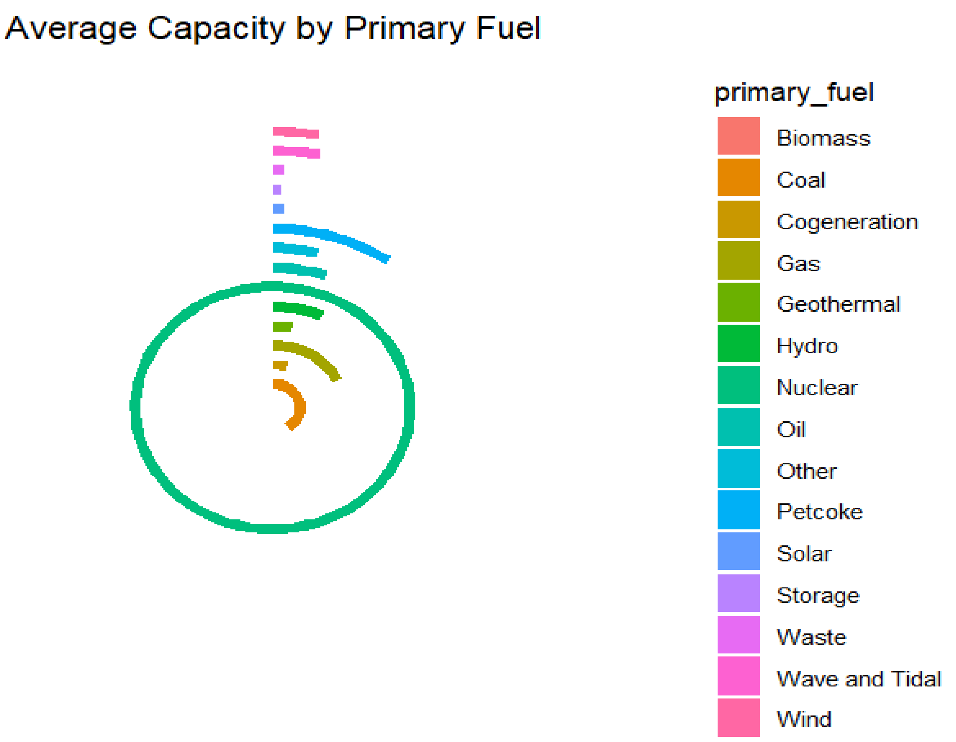


Figure-7

Here we can see that nuclear energy is miles ahead in efficiency per plant but only has 195 plants. May because of the added risks it comes with including dumping waste after nuclear reactor retires, mistakes in operation can cost millions and harm lives. Construction of nuclear plants is therefore generally done in remote areas away from civilization. The second most efficient fuel seems to be Pet coke with only 12 plants. Pet coke is by-product of residuals from petroleum refining. But if burned, due to high amount of Sulphur it can produce acid rain. Therefore, it needs to be gasified to provide cleaner energy. Unsurprisingly solar, wind, and hydro plants produce less energy per plant. Solar being the worst out of it. Wind and hydro plants also need favorable weather conditions to produce more, and humans can't control nature. Wind plants need to be in very specific windy open fields where land isn't used for more important purposes like agriculture, and they also must be maintained. On top of that many days aren't as windy as others. Hydro plants require specific high-water flow and geological locations should be capable enough to sustain these large construction projects.

Discussion:

Electricity being a huge part of modern society is very important as are the resources used to produce it. Many resources in production of electricity harm the environment and while others are more sustainable. There is a global push of transitioning to renewable energy otherwise the planet would be in danger due to global warming and climate change caused by ignorance. Obviously use of pollution causing non-renewable sources of energy like Coal, Oil and Gas to accelerate this process that at the moment we can't reverse.

In this report we saw that population is often not the indicator of energy produced by the country (Figure 1). Apart from the reasons discussed above it may be that there are more frequent power cuts in some areas of developing countries and some even to this day don't receive basic electricity.

As the report moves forward we see that very less data is available and most of it is estimated through models. But for these models to estimate data we need data in the first place. Fortunately original production data for some renewable sources was actually available with this and models estimated for all similar fuel types were filled. But unfortunately data for non-renewable sources isn't available at all, so models are useless here. There might be a reason this data isn't public, perhaps these companies or government or both don't want to be open about how much of their country is powered by pollution causing renewable sources. On the other hand they provide data for all renewable sources and on top of that there are a high number of renewable energy plants. Despite this high number of plants, their energy capacity is lesser compared to other renewable sources. It is possible that these plants are cheaper to open, especially solar energy ones, because there is a huge discrepancy in number and capacity of these. Hydro and Wind plants still look bad but Solar plants are on whole another level. Maybe this is because they show that they care about renewable energy and because solar plants are cheaper to open rather than Hydro and Wind (Evans 2020).

We can also see how top countries change when we go from estimated to capacity data from Figure 4 to Figure 6. We can only see solar because of its theoretical maximum capacity and really high number of plants. We can even see that Oil and Gas numbers are also significant despite the lesser number of plants in the data. This actually includes the capacity of plants with secondary fuel which most commonly are Oil and Gas. We don't have different capacity figures for each fuel type for plants that use more than one fuel type. Solar, Hydro and Wind plants might or might not have higher production through other fuel like Oil or Gas. Same goes for all other energy sources.

I wanted to find research for just non-renewable sources for energy production but most papers out there only have word non-renewable while they are comparing its impact to renewable sources, negative economic impacts of it (Mohammadi, Saghaian and Gharibi 2023) or negative environmental impacts (Ansari 2017). It is really hard to get the actual number of electricity generated by non-renewable sources.

Many countries still rely on huge Oil, Coal and Gas plants for main sources of their energy, despite efficiency of other fuels like Nuclear and Pet coke being really high. These do come with added risk and Nuclear energy requires proper handling and Pet coke is a by-product of petroleum so not everyone has access to it. The Radial graph (Figure 7) also reveals that Gas and Coal are also really efficient despite harming the environment. Solar energy here is especially really weak despite the huge number of plants using it. Other energy sources like Wave, Tidal, Geothermal, and Wind need high amounts of research to increase their viability and efficiency. This can really show companies and governments that they can meet energy demands without accelerating climate change. There is absolutely tons of research being put in this field already.

If data had completed columns, the report would have really compared all fuels and what is actually fulfilling the world's demand for energy. If this type of data is made available people can truly see how reliant we are still on non-renewable energy. This can raise concerns and boost and promote research towards a better planet. At the end there will be more net positives than negatives if everything is made clear.

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