Method for Calculating the Uncertainty range of Avoided Primary Energy Consumption and Environmental Impact applied to Data Analysis Software Services and Solar Electricity

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Abstract: - The absolute and avoided primary energy consumption (PEC) of Software (SW) services is getting more attention. However, there is no commonly agreed bottom-up methodology for calculation of the total PEC of SW services. Life Cycle Assessment (LCA) is a common denominator for most existing methodologies. The purpose is to test a new simplified methodology which includes the uncertainty and sensitivity. The new methodology is applied to two illustrative cases: data analysis SW and electricity production. The baseline results for data analysis SW show that the uncertainty will be quite high at around 30% and the most sensitive parameters are the production of electricity, the amount of data transfer and the production of the end-user device.
Moreover - the data bytes transferred from the end-user device per iteration, the PEC per byte data transfer and the PEC of the production of the end-user device used to access the SW - contribute most to the total uncertainty. Regarding solar electricity replaced by a proportionate electricity mix, the avoided carbon emissions in China from 2021 to 2023 were 80±36 million tonnes. Intermediate suppliers to the solar electricity production systems can claim to have contributed to the avoided emissions according to their contribution ratio.

Key-Words: - avoided impact, data analysis, environmental impact, solar electricity, software, uncertainty, life cycle assessment.

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1 Introduction

For several years there has been a growing interest to attempt to find the primary energy consumption (PEC) associated with software (SW) solutions [1] such as individual SW, packages, middleware, and operating systems [2]-[26].

SW production impacts can be caused by the use of electricity in turn used by offices and computers used by the SW designers [7].
SW systems use energy through the manufacturing and use of the hardware that they operate on [15].
SW service Life Cycle Assessment (LCA) includes resources such as terminals, software, networks, service platforms, and servers. Many SW programs are currently run in the cloud with data transfer from data centers via networks to end-user devices.
The LCA methods proposed in [27,28] for cloud services are less to the point for cloud SW than the present method which is somewhat more practical.
Most research in this domain uses descriptive approaches and point out the challenges but recently more methods have emerged [9,15,16,20]. It is not clear how the all the input data for such methods can easily be collected. Here is presented a hands-on methodology for SW applied to cloud SW services with an accompanying case study. Moreover, avoided impact methods including probability analysis have not been applied to data analysis software services. The hypothesis is that the data analysis software service use around 100 Wh PEC per hour.
Another trend is that Solar electricity has grown to change the electricity generation system helping avoid environmental impacts (EI) from other power

sources [29]. However, avoided emission analyses including probability have not so far been applied to solar electricity. How much carbon emissions were avoided in China between 2021 and 2023 in China due to solar electricity? Here a suggestion of probable avoided EI from Solar growth in China from 2021 to 2023 is attempted. The probability methodology used in the present research is further described in [30].

2 Materials and Methods

This section describes how the total EI of a specific SW Service can be calculated with minimal effort but still explain the important drivers. It also describes how avoided EI from solar electricity can be calculated in the interest of intermediate suppliers and end-user solution providers both.

2.2 Primary energy consumption of software services

The main PEC of a SW service can be estimated by adding the end-user device use and production, the data transfer use and the data centers use stage.

The function of the present SW service is to provide visualization of data analyses.
The functional unit is “A subsystem enabling visualization of one analytical iteration by one employee with a data analysis software.”

2.2.1 End-user device use stage

This stage concerns the use of electrical energy in the use stage for the end-user device used to access the SW service. For simplicity one contemporary laptop (and no other devices) is assumed to be used to run the data analysis software. The laptop battery capacity is around 80 Wh electricity [31] and its uncertainty range is set to 15 Wh. The battery life when 100% fully charged is assumed to be 8 hours with uncertainty range 3 hours [32].

The duration of one iteration is 20 seconds with uncertainty range 3 seconds and the global average electricity production use 2.7 Wh PEC/Wh±0.2 Wh/Wh.

Then the PEC of the use of the end user device is calculated as:

2.7 Wh PEC/Wh×20 seconds×80 Wh/[8×3600 seconds] = 0.15±0.063 Wh PEC/analytical iteration.

It would be possible to add more devices such as smartphones and desktops to this section.

2.2.2 End-user manufacturing stage

The laptop manufacturing impact is around 1 million Wh PEC per piece and the uncertainty is 0.5 million Wh [33]. Other assumptions are that 35%±5% of the laptop capacity is used during the iteration, the lifetime of the laptop is 4±2 years [34], and the working hours per year are 2000±50 hours. Then the PEC of the production of the end user device is calculated as:
1.018 million Wh/laptop×20 seconds×35%/[4 years/laptop×8 hours/day×5 days/week×50 weeks/year×3600 seconds] = 0.247±0.183 Wh PEC/analytical iteration.

The uncertainty range for manufacturing is very large due to the variable lifetime of the device and the EI per device.

Similarly, to section 2.2.1, it would be possible to add more devices such as smartphones and desktops to this section.

2.2.3 Data transfer use and manufacturing stages

The analysis results are transmitted via various networks. The scope for data transfer includes a fraction of the complete internet infrastructure including when it is not used but still running. Supporting infrastructure significantly enables the operation of software [7]. Such infrastructure could include:
— Compute resources
— Storage
— Networking equipment
— Memory
— Monitoring
— Idle machines
— Logging
— Scanning
— Build and deploy pipelines
— Testing
— Training Machine Learning models
— Operations
— Backup
— Resources to support redundancy
— Resources to support failover
— End user devices
— Internet of Things-devices
— Edge devices.

This supporting infrastructure is the reason why the entire Internet electricity intensity is used in this segment.
The electricity use of data transfer is around 0.223 ±0.055 Wh/MegaByte [35]. 0.223 is obtained from year 2024 in [35] as 2008 TWh divided by 8796 ExaByte divided by 1024 times 1000. On average around 2±0.5 MegaBytes are transmitted per iteration.

Then the EI of the data transfer is calculated as:

2.7 Wh PEC/Wh×0.223 Wh/MB×2 MB/iteration = 1.204±0.434 Wh PEC/analytical iteration.

The uncertainty range for the data transfer is very large mainly due to the Wh/MB and amount MB per iteration.

Moreover, the data transfer impact might occasionally be reduced via the design of the SW solution:

2.7 Wh PEC/Wh×0.223 Wh/MB×0.5 MB/iteration = 0.3±0.108 Wh PEC/analytical iteration.

2.2.4 Cloud use stage

The data centers play a major role for the SW services like visualization of data analyses. One iteration is assumed to require 8±2 virtual Central Processing Units (CPUs) and 64±4 GigaByte Memory over 0.5±0.2 seconds. The electricity consumption is assumed to be $7\times10^{-4}\pm1.4\times10^{-4}$ Wh/s per virtual CPU [36] and $1.25\times10^{-4}\pm2.5\times10^{-5}$ Wh/s per GB for memories [37]. A virtual Graphical Processing Unit (GPU) might use more power than a virtual CPU [38] but this is not explored further. Then the PEC of the cloud use is calculated as:

2.7 Wh/Wh×0.5 seconds/iteration×[8 virtual CPU×0.0007 Wh/s/CPU + 64 GB/iteration × 0.000125 Wh/s/GB] = 0.0184±0.0062 Wh/analytical iteration.

The time used for each iteration (0.5 seconds) contributes the most to the uncertainty range for the cloud use.

2.2.5 Summary

By the building blocks mentioned in sections 2.2.1-4 it is possible to calculate the PEC from one iteration and also the avoided PEC by more or less data transfer.

The total energy use for the baseline product is 1.62±0.477 Wh PEC/analytical iteration.

Moreover, 1.62 Wh PEC per 20 seconds duration of one iteration → 291.6 Wh PEC/hour.

The total energy use of a lower EI design (target product) is 0.717±0.214 Wh PEC/analytical iteration.

Potentially avoided PEC from this particular data analysis SW are:
1.62 Wh/iteration – (1+0.378)×0.717 Wh/iteration = 0.632 Wh±0.381 Wh. The calculation includes a 30% rebound effect, i.e. (0.378×0.717)/(1.62-0.717). The uncertainty is 60.3% around the mean.

2.3 Solar electricity avoided emissions

Electricity generation is one of the most analyzed systems in LCA [39].

In China, Solar electricity generation grew by 257.2 TWh (78.6%) between 2021 and 2023 [40,41]. However, it is not clear which source of electricity this growth replaced for this time period.
Apart from Solar, the predominant sources for power production in the Chinese market are Coal, Hydro, Wind, Nuclear, and Gas. The average of those five is a reasonable assumption for which technologies Solar replaced between 2021 and 2023. However, the allocated mix by is difficult to quantify.

For the present research the function is to provide electricity.
The functional unit is “A subsystem providing 257.2 TWh electricity in China between 2021 and 2023.”

Anyway, 0.5 kg CO_2e/kWh can be used as a rough approximation if the factor for a certain country cannot be obtained [42]. 0.12 is assumed as uncertainty range.
Average solar electricity releases between 37.3 and 72.2 grams CO_2e/kWh [43] with an average of 54.75.

Then the avoided EI per functional unit of the Solar electricity growth is:

252.7 billion kWh × [0.5 kg CO_2e/kWh for average mix – 3.44×0.05475 kg CO_2e/kWh for Solar] =

8.016E+10 kg CO_2e = 80.16 million tonnes±36.3 million tonnes. The calculation includes a 30% rebound effect, i.e. (252.7 billion×2.44×0.05475)/(252.7 billion×0.5-252.7 billion×0.05475). The uncertainty is 45.3% around the mean.

The rebound effect is the potential benefit minus the actual benefit. To have a rebound effect of 30% for this system, 2.44 times the impact of the solar electricity has to be deducted from the potential avoided emissions.

The approach is also applicable to year by year estimations of avoided EI.

3 Results

3.1 Data analysis software services
The results are shown in Figures 1, 2 and 3.

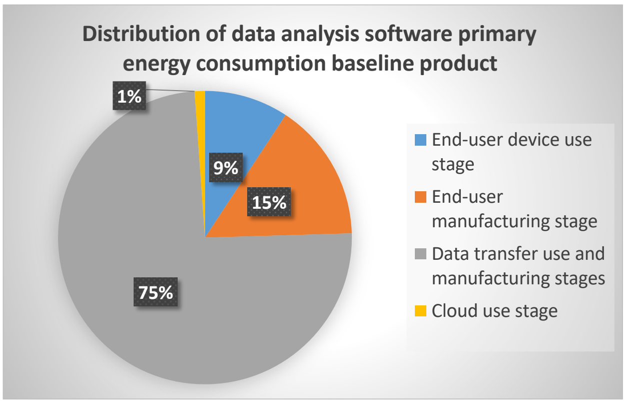

Fig. 1. Impact from SW service baseline product.

The total result is 1.62±0.477 Wh PEC/analytical iteration.

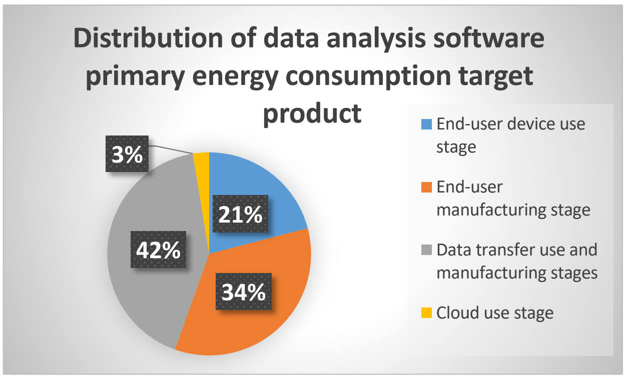

Fig. 2. Impact from SW service target product

The total result is 0.716±0.214 Wh/analytical iteration.

In Figure 3, the amount of data transferred per iteration and the amount of Wh used per MB contribute altogether 90% to the total uncertainty for the avoided PEC.

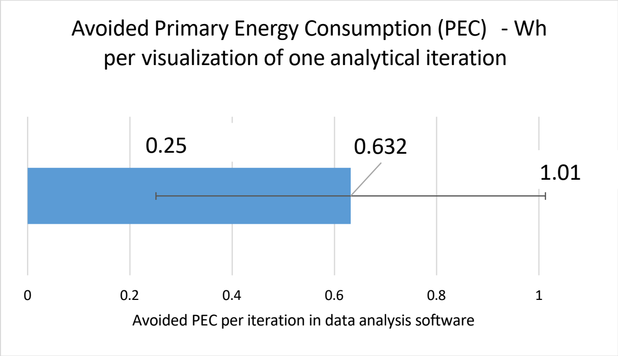

Fig. 3. Avoided primary energy consumption from introducing new data analysis software.

3.2 Solar electricity

Figure 4 shows that the probability is very high that solar electricity growth helped avoid emissions.

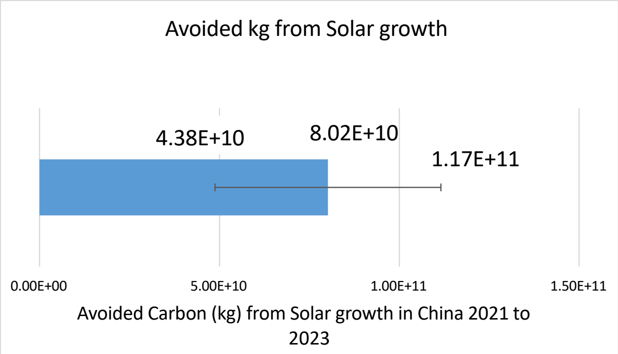

Fig. 4. Avoided emissions from Solar electricity growth 2021 to 2023 in China.

The EI/kWh uncertainty contributes 72% to the total uncertainty of 36.3 million tonnes.

4 Discussion

There is likely some typical ballpark numbers for PEC energy consumption for software services e.g. Joules per GB and per hour. It would be unreasonable to diverge too much from $\approx 10^2$ Wh/hour and $\approx 10^1$ Wh/GB. Anyway, cloud video streaming software services have several benchmarks such as [27] at around 30 Wh electricity/GB and 72 Wh electricity/hour. Another is Fig. 2 in [10] at 83 Wh PEC/GB and 250 Wh PEC/hour for streaming, as well as 1440 Wh PEC/hour [9] and 142 to 1220 Wh PEC/hour [21].

As shown in Figure 5 the present baseline iteration (292 Wh PEC/hour) corresponds to around 1.5 GB/hour of video streaming.

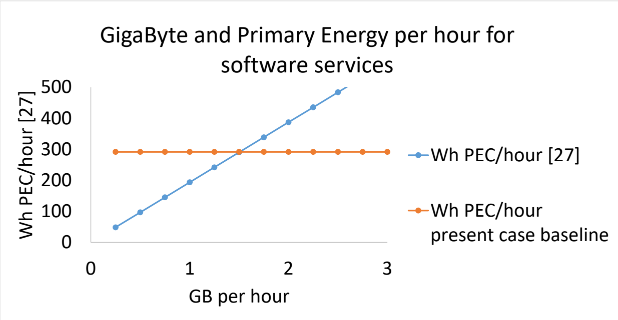

Fig. 5. Typical relation between data consumption and primary energy per hour for software services.

Regarding global annual cloud electricity use, is the present 0.000125 Wh/s per GB (0.45 W/GB) for memories consistent with [3] for data centers (0.007 kWh/GB) which led to 400 TWh electricity per year?

It has been estimated that globally 0.33 ZettaByte (363 billion GigaByte) of data are generated daily [37].

As a sanity check for electricity consumption related to data generation in data centers:

0.45 (J/s)/GB × 3.63E+11 GB data generated globally/day [37] × 86400 s/day = 1.41E+16 J/day = 3.92 TWh electricity/day leading to 1430 TWh electricity per year which is a kind of reasonable - but still much too high - ballpark number. The reason is that not all data generated use 0.45 W/GB.

This uncertainty is reflected in section 2.2.4 for the CPUs.

The data transfer energy efficiency is increasing with every new technology introduced [44]. Such phenomena could change which parts of the SW lifecycle are most important from an energy standpoint.

To this point, Artificial Intelligence data analysis SW [20] might have a different distribution of the impacts than shown in Figures 1 and 2. Cloud use probably has a higher share for AI SW services than non-AI SW.

Solar electricity helps avoid emissions but so far there is no agreed method for allocation to different processes in the ecosystem. Depending on the solar solution features, PV modules and inverters and occasionally batteries are necessary for the function of the Solar Solution. Then the intermediate manufacturers of PV modules, inverters, batteries and the Solar system provider itself may claim shares of the avoided emission. These shares might be based on different contribution keys and ratios still to be developed.

Avoided impact scores are very dependent on use case and geography. The variation of such cases should be investigated.

5 Conclusions

Avoided PEC and EI calculations are straight-forward and can be done in a streamlined manner. Simplified approaches for SW Service impact evaluations are relatively accurate for early design stage trade-off potentials.

6 Next steps

It remains to be researched whether the developed method is generally applicable to SW Services beyond data analysis.

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