energies

MDPI

Article

Uncertainty of the Electricity Emission Factor Incorporating the Uncertainty of the Fuel Emission Factors

Kun Mo LEE [1,*] and Min Hyeok LEE [2]

[1] Department of Environmental and Safety Engineering, Ajou University, 206 Worldcup-ro, Yeongtong-gu, Suwon-si 16499, Korea
[2] Global Manufacturing Center, SHE Group, Samsung Electro-Mechanics, 150, Maeyeong-ro, Yeongtong-gu, Suwon-si 16674, Gyeonggi-do, Korea; robertee2@gmail.com
* Correspondence: leekunmo@gmail.com; Tel.: +82-10-3082-2887; Fax: +82-31-219-1613

Abstract: Greenhouse gas (GHG) emission from electricity generation has been recognized as one of the most significant contributors to global warming. The GHG emission factor of electricity (hereafter, electricity emission factor) can be expressed as a function of three different (average, minimum, and maximum) fuel emission factors, monthly fuel consumption, and monthly net power generation. Choosing the average fuel emission factor over the minimum and maximum fuel emission factors is the cause of uncertainty in the electricity emission factor, and thus GHG emissions of the power generation. The uncertainties of GHG emissions are higher than those of the electricity emission factor, indicating that the uncertainty of GHG emission propagates in the GHG emission computation model. The bootstrapped data were generated by applying the bootstrap method to the original data set which consists of a 60-monthly average, and minimum and maximum electricity emission factors. The bootstrapped data were used for computing the mean, confidence interval (CI), and percentage uncertainty (U) of the electricity emission factor. The CI, mean, and U were [0.431, 0.443] kg CO_2-eq/kWh, 0.437 kg CO_2-eq/kwh, and 2.56%, respectively.

Keywords: GHG emission; electricity emission factor; fuel emission factor; uncertainty; bootstrap

check for updates

Citation: LEE, K.M.; LEE, M.H. Uncertainty of the Electricity Emission Factor Incorporating the Uncertainty of the Fuel Emission Factors. *Energies* **2021**, *14*, 5697. https://doi.org/10.3390/en14185697

Academic Editor: Adriano Sacco

Received: 20 July 2021
Accepted: 6 September 2021
Published: 10 September 2021

Publisher's Note: MDPI stays neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Copyright: © 2021 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https://creativecommons.org/licenses/by/4.0/).

1. Introduction

The greenhouse gas (GHG) emission factor of electricity (hereinafter, electricity emission factor) has been used widely to quantify GHG emissions from the generation and use of electricity [1]. GHG emissions from electricity generation and use are one of the most significant sources of GHG emissions in the world [2–6]. In particular, according to U.S. Energy Information Administration (USEIA), in 2019 the total U.S. electricity generation by the electric power industry was 4.13 trillion kilowatt-hours (kWh) from all energy sources, which resulted in the emission of 1.72 billion metric tons of CO_2. To be specific, power plants that burned coal, natural gas, and petroleum fuels were the source of about 62% of total U.S. electricity generation, but they accounted for 99% of U.S. electricity-related CO_2 emissions. The other 1% of CO_2 emissions came from other fuels and gases derived from fossil fuels and some types of geothermal power plants. USEIA considers electricity generation from biomass, hydro, solar, and wind to be carbon neutral [7].

A challenge of the environmental assessment of a power system is the steady variability of electricity generation due to the variabilities of the demand, some production sources such as renewable sources, and the set of technical constraints [8]. Marginal electricity generation has been considered an important application to meet strong seasonal and diurnal variation in electricity demand [9]. Although there is a notable difference among different electrical grids, Collinge et al. [9] observed that resource mix and regional grid systems are particularly important for any LCA involving the use phase of buildings, which was supported consistently by similar findings [9].

The marginal emissions are the emissions that would come online if the new load was added. When electricity load surges and thus the marginal power plant is in operation, GHG emission from the marginal plant is usually higher than normal plants. Thus, the marginal emissions factor, which is the change in CO_2 emissions relating to a unit change in electricity demand, needs to be secured [10].

The marginal emission factor is the emission factor of the marginal electricity, which is the electricity generated by all the marginal sources [11]. There are two types of emission factors in use: the global emission factor representing the average emission rate of the power grid (of all power generators) and the marginal emission factor representing the emission rate of the power grid due to a change in the power demand (emission rate of the marginal generators) [12]. The electricity emission factors in this paper are the average emission factors (global emission factor), which is the average CO_2 emissions per average unit of electricity delivered for an entire electrical system.

In the consequential LCA (CLCA) where the product system expansion is used to avoid allocation, the marginal emissions including the marginal electricity emission have a strong influence on the LCA results [13]. As such, the proper marginal electricity emission factor is a crucial element to the accuracy and reliability of the CLCA results.

There are uncertainties associated with the average (global) and marginal emission factors. Kono et al. [14] highlighted potential underestimation and overestimation of emissions by using the annual average emission factor which ranged from +22% (weekday nighttime of October 2015) to −34% (weekend daytime of May 2015). They suggested that the application of hourly emission factor may be necessary to quantify the respective emission from the consumers that use electricity during the weekend daytime and weekend nighttime. For consumer use at other times, the emissions could be quantified appropriately by using the conventional annual average emission factor [14].

Assessing the uncertainty enables the comparison of different information and communication technology (ICT) systems. The IEEE [15] compared two ICT systems with different uncertainties: 23.8 +/− 3% versus 25.3 +/− 20%. If expressed in a confidence interval (CI), the former can be [23.1, 24.5], the latter [20.2, 30.4]. Assuming that the confidence level of both cases is equal (e.g., 95%), the CI width overlaps such that one cannot claim that the former is different from the latter. In this case, however, the latter has the percentage uncertainty (U) of 40.3%, while the former has 5.9%, which shows that the latter has 6.8 times higher uncertainty than that of the former. This indicates that direct comparison between the two may be problematic. Nonetheless, this example shows an important application of the uncertainty information to ascertain which product system emits less GHG emissions.

The electricity emission factor has been presumed constant in many parts of the world. For instance, 0.957 tCO_2/MWh, 0.928 $kgCO_2$-eq/kWh in South Africa, 0.555 $kgCO_2$-eq/kWh in China, 0.708 $kgCO_2$-eq/kWh in India, 0.506 $kgCO_2$-eq/kWh in Japan, 0.495 $kgCO_2$-eq/kWh in Korea, 0.8800 $kgCO_2$-eq/kWh in Australia, 0.4258 $kgCO_2$-eq/kWh in the United Arab Emirates, 0.13 $kgCO_2$-eq/kWh in Canada, 0.45322 $kgCO_2$-eq/kWh in the United States, 0.074 $kgCO_2$-eq/kWh in Brazil, etc. [16–21]. However, it can also be considered a random variable [22,23]. Lee et al. [22] compared the effect of the feedstock emission factors under the constant and random variable assumptions in quantifying GHG emissions from dairy farms [24,25].

For the electricity emission factor case, the factor was treated as both constant and random variable [26]. In general, the electricity emission factor varies continually because of the variations in fuel consumption and net power generation, and the presence of other powers such as the nuclear and renewable powers in the electricity grid [27,28]. Fossil fuel consumption for power generation varies continually due to variations in power generation. The variation comes from several sources including demand for power (either higher or lower demand), the shutdown of the power plant due to repair and maintenance, and changes in the power grid, etc. [28–34].

The electricity emission factor, Y, is a function of various random variables (i.e., here factors). Some of the factors may be dependent on each other, such as ambient temperature and demand for cooling. However, there are independent factors such as industrial production/consumption, ambient temperature, fuel mix, fuel composition, among others. Since an electricity emission factor is a function of (depends on) these independent random variables, the factor can be considered an independent random variable. However, it may also be considered an independent random variable as an approximation. This is because there are so many factors at play and some factors are interrelated or duplicative such that independence among the numerous factors cannot be ensured. Thus, we consider the electricity emission factor an independent random variable as an approximation.

The objective of this paper is to (1) assess the effect of three different fuel emission factors (average, minimum, and maximum) on the electricity emission factor and (2) propose a modified approach for computing the electricity emission factor based on the bootstrapping simulation which incorporates three fuel emission factors, fuel consumptions, and net power generation.

2. Materials and Methods

Fossil fuel consumption data for generating power in Korea from January 2015 to December 2019 were collected from the website of the Korea Electricity Corporation [28]. Four different types of fossil fuel for power generation include: Anthracite coal, Bituminous coal, Heavy oil, and Liquified Natural Gas (LNG). For each type of fuel, we collected the monthly fuel consumption (GJ) and power generation (Gwh) data. In addition, the total power generation data in the Korean electricity grid, including the nuclear and renewable powers during the same time period, were also collected. The in-plant power consumption and transmission loss data were available in the form of the percentage of the total power generation.

Equation (1) is an equation to calculate the net power generation factor from the entire electricity grid. The Korean electrical grid is a single grid.

$$\text{Net power generation factor} = 1 - \text{ft} - \text{fp} \tag{1}$$

where,

ft = transmission loss factor

fp = in-plant loss factor.

The values of the ft and fp in Equation (1) were given by the power generator as the average during the five-year period. As such, they are constants. Equation (2) was used to compute the net power generation from the entire electricity grid by multiplying the net power generation factor to the total power generation of the grid mix.

$$\text{Net power generation} = (1 - \text{ft} - \text{fp}) * \text{total power generation, Gwh} \tag{2}$$

Equation (3) is based on the Tier I approach for computing the electricity emission factor for the single electricity grid [35].

$$\begin{gathered}\text{Electricity emission factor (Tier I approach)} = \\ \text{average fuel emission factor} * \text{fuel consumption/net power generation}\end{gathered} \tag{3}$$

The GHG emission factor of fuels is termed as fuel emission factors in this paper. Table 1 lists the average, minimum, and maximum values of the fuel emission factor [35]. For fossil fuel combustion, uncertainties in CO_2 emission factors are relatively low. However, there are likely to be intrinsic differences in the uncertainties of CO_2 emission factors of petroleum products, coal, and natural gas. Emission factors for CH_4 and especially N_2O are highly uncertain. Default uncertainty estimates of CH_4 vary from 50 to 150%, and that of N_2O is on the order of magnitude. Such variability obviously will also contribute to the uncertainty in the emission estimates [35].

Table 1. Fuel emission factor (kg CO_2-eq/kg fuel).

Gas	Anthracite	Bituminous	Heavy Oil	LNG
CO_2 avg	98,300	94,600	74,100	64,200
CO_2 min	94,600	89,500	72,600	58,300
CO_2 max	101,000	99,700	74,800	70,400
CH_4 avg	32	32	96	96
CH_4 min	10	10	32	32
CH_4 max	96	96	320	320
N_2O avg	447	447	179	179
N_2O min	149	149	60	60
N_2O max	1490	1490	596	596

Equation (3) uses the average fuel emission factor of each fuel type listed in Table 1, and fuel consumption/net power generation of each fuel type [27,28]. The average fuel emission factor for Bituminous coal, for instance, is the sum of CO_2 avg, CH_4 avg, and N_2O avg of the Bituminous column where 94,600 + 32 + 447 = 108,904 kg CO_2-eq/kg Bituminous coal.

The uncertainty of emission factors has been considered a major challenge to the estimation of GHG emissions by the Intergovernmental Panel on Climate Change (IPCC). The IPCC recommends reporting a mean estimate of the GHG emissions as the point estimate. The uncertainty analysis focuses on the quantification of the random errors with respect to the mean estimate using the classical inference statistics, such as the 95% confidence interval (CI) here [36]. They recommend reporting the uncertainty as the percentage uncertainty (U) where U is the ratio of the half-width ((the upper bound–lower bound of the CI)/2) divided by the mean of the two bounds in percent [36].

In this study, we adopted the IPCC approach in reporting and comparing the uncertainty with respect to U. In addition, we advocated in this paper that use of a point estimate can be misleading without U. Most of the electricity emission factors reported a point estimate without U. As such, we prefer to report the electricity emission factor and GHG emissions with respect to the 95% CI and U, although we report the point estimate at the same time. The main point here is that a point estimate alone is misleading, for it imparts the notion that the electricity emission factor and GHG emission is a single value. The fact is that the true mean (unknown) lies between the lower bound and upper bound of the CI for 95% of the time. A point estimate is one of the many possible values of the electricity emission factor and GHG emission within the CI such that their accuracy cannot be estimated by the point estimate alone.

Interval estimate using the 95% CI approach based on the observed data is often used in estimating the CI of the electricity emission factor and GHG emission [36,37]. Stochastic simulation improves the accuracy of the interval estimate; thus, use of the stochastic simulation method such as the bootstrap method [38–41] is necessary. In this study, the bootstrap method was used to obtain the CI of the electricity emission factor and GHG emission.

We propose an approach in this paper to obtain the electricity emission factors. Equation (4) is the proposed approach for computing the electricity emission factor as a function of the three different fuel emission factors, monthly fuel consumption, and monthly net power generation.

$$Y = AX \tag{4}$$

where,

Y = electricity emission factor (proposed approach), kg CO_2-eq/kwh,
A = fuel emission factor matrix, kg CO_2-eq/MJ fuel,
X = random variable vector = $\{X_1, X_2\} = X_1/X_2$,
X_1 = fuel consumption per fuel type, MJ/fuel type,
X_2 = net power generation, kwh.

As shown in Equation (4), only X_1 and X_2 are random vectors. The A matrix, ft, and fp are constants. In Equation (4), the A matrix (matrix size: 9 × 4 = 36) is the same as shown in Table 1. The X random variable vector consisting of two random variables, X_1 and X_2, represent the monthly fuel consumption and monthly net power generation of each fuel type, respectively. The X_1 vector has 60-monthly fuel consumption data of the four types of fuels (60 × 4 = 240), and the X_2 vector has 60-monthly net power generation data of the four types of fuel (60 ×4 = 240), each in a matrix form.

The three fuel emission factors (minimum, average, and maximum) in matrix A are independent of each other; thus, all computations of the electricity emission factors based on the three fuel emission factors were made independently. Therefore, there are three different electricity emission factors obtained from Equation (4).

When calculating the CI of the electricity emission factor, bootstrapping was applied to X_1 and X_2, while keeping A matrix constant to generate the bootstrapped data for each of the three electricity emission factors. As such there are different CI and U for each of the three-electricity emission factors.

The bootstrapping gives narrower CI, as such it increases accuracy of the Y compared to the non-bootstrapping case (e.g., using raw data for computing Y) [21–23,42]. A computer program was coded using R, a programming language specialized in statistics, to compute the electricity emission factors and GHG emissions based on the bootstrap method [39].

The reason for choosing five latest years for the time period is that the mean yearly electricity emission factors were relatively similar (0.429, 0.439, 0.444, 0.432, 0.436) during this time period, indicating that the fuel consumption/net electricity generation during the same time period remains relatively flat. The reason for using the monthly average electricity emission factor is that there are neither daily nor weekly average electricity emission factors available. If daily or weekly data were available, these data can be used in lieu of the monthly data to reflect continual fluctuation of the type and amount of fuel consumption per net power generation.

The time period of the Tier I approach, however, is not transparent. Often there is no disclosure of the time period covered and the number of data used [43]. In fact, most of the electricity emission factors in the literature are not transparent and do not disclose the time period and the number of data used [17,19,20].

The difference between the proposed approach and the Tier I approach can be summarized as (i) use of the three different (average, minimum, and maximum) fuel emission factors versus the average fuel emission factor, and (ii) specified time period of the fuel consumption and known number of data used versus unspecified time period and unknown number of data used.

GHG emission computation equation in Equation (5) is a product between the electricity emission factor and the net power generation.

$$\text{GHG emission} = \text{electricity emission factor} * \text{net power generation} \quad (5)$$

The relative difference (RD) is defined as the half-width between the maximum and minimum values divided by the average value as shown in Equation (6). Conceptually the RD is similar to the U defined in IPCC [36].

$$\text{RD} = (\text{maximum value-minimum value})/(2 * \text{average value}) * 100 \quad (6)$$

3. Results and Discussions

Figure 1 shows the variation of several factors including the transmission loss (a), in-plant loss (b), net power generation factor (c), and power generation factor (d) over the 60-month period from 2015 to 2019. The power generation factor includes the net power generation factor as well as the transmission plus in-plant loss factor.

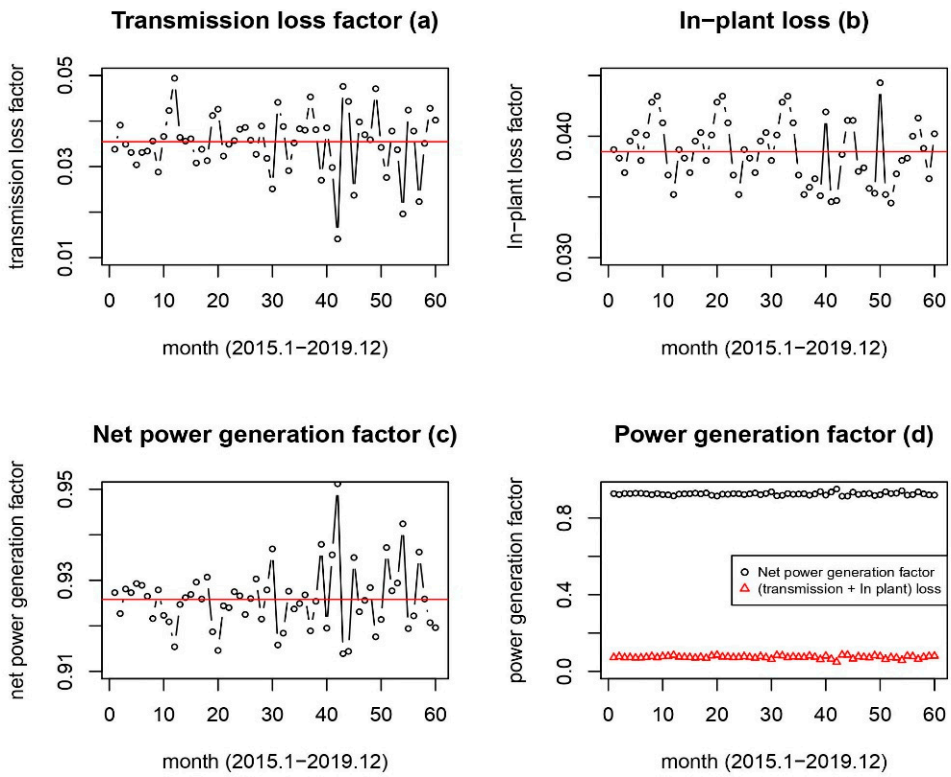

Figure 1. Variation of the transmission loss (**a**), in-plant loss (**b**), net power generation factor (**c**), and power generation factor (**d**).

The transmission loss factor (a) and in-plant loss factor (b) vary considerably over the months. As such, the net power generation factor (c) also varies considerably. Figure 1d shows both the net power generation factor and the transmission plus in-plant loss factor, where the value of the former is 0.926, while the latter 0.074. Thus, approximately 7.4% of the total power generated is lost, and only 92.6% is used by the end-user, which is the net power.

Figure 2a shows the fossil fuel consumption during the 60-month period. Bituminous coal was the fuel consumed most (77.1%), followed by LNG (19.2%), Heavy oil (2.3%), and Anthracite coal (1.4%). Total energy consumption of fossil fuels for 5 years was 12,538,220 TJ, or 2,507,644 TJ/year. The total fossil fuel consumption varies considerably from month to month, most fluctuations occur in the Bituminous coal and LNG consumption. Figure 2b shows that the monthly net fossil fuel power generation. It fluctuates considerably over the 60-month period.

The monthly electricity emission factors (average, minimum, and maximum) were plotted in Figure 3a. The three fuel emission factors (minimum, average, and maximum) in matrix A were multiplied by common elements of X vector (X_1/X_2) to generate three different electricity emission factors from Equation (4). An assumption made in Equation (4) is that no GHG emission occurs from the nuclear and other sources of power generation processes. We will use the term average electricity emission factor as the one based on the average fuel emission factor. The same applies to the minimum and maximum electricity emission factors. Figure 3a shows that the average, minimum, and maximum electricity emission factors fluctuate considerably over the month. Figure 3b shows that the monthly GHG emissions based on the average, minimum, and maximum electricity emission factors fluctuate considerably over the month. Figure 3b indicates a similar trend as that in Figure 3a. However, the degree of fluctuation is more prominent compared to that in Figure 3a.

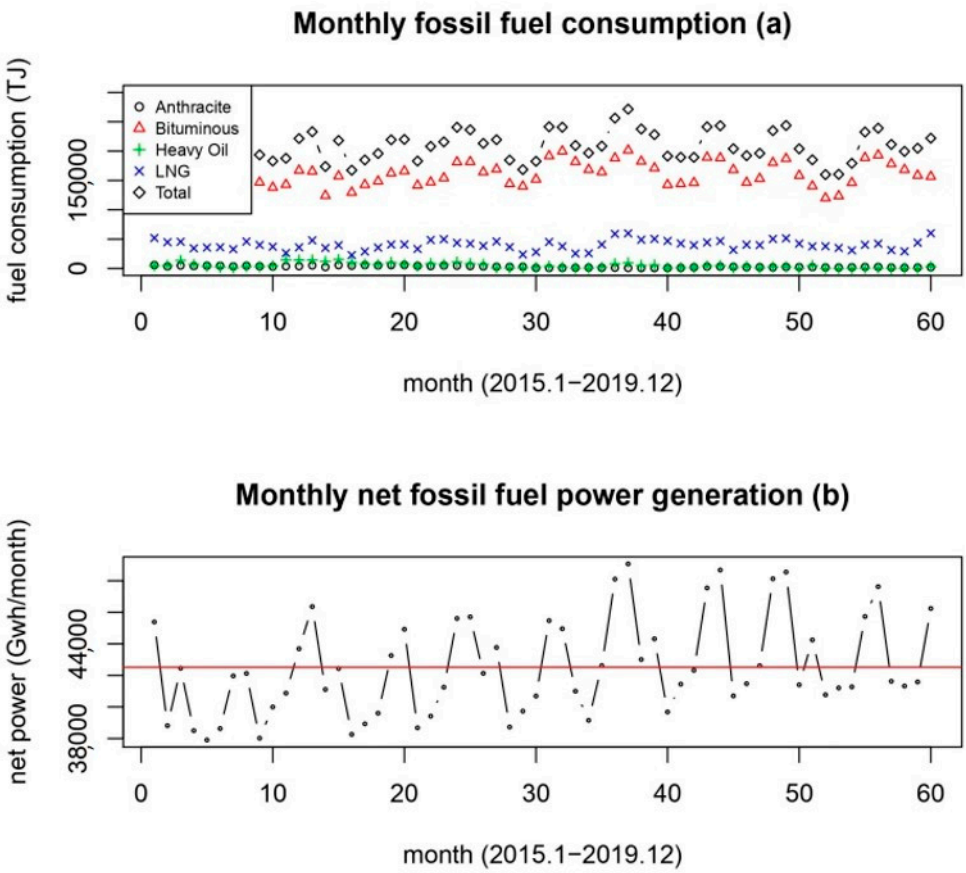

Figure 2. Monthly fossil fuel consumption (**a**) and monthly net fossil fuel power generation (**b**).

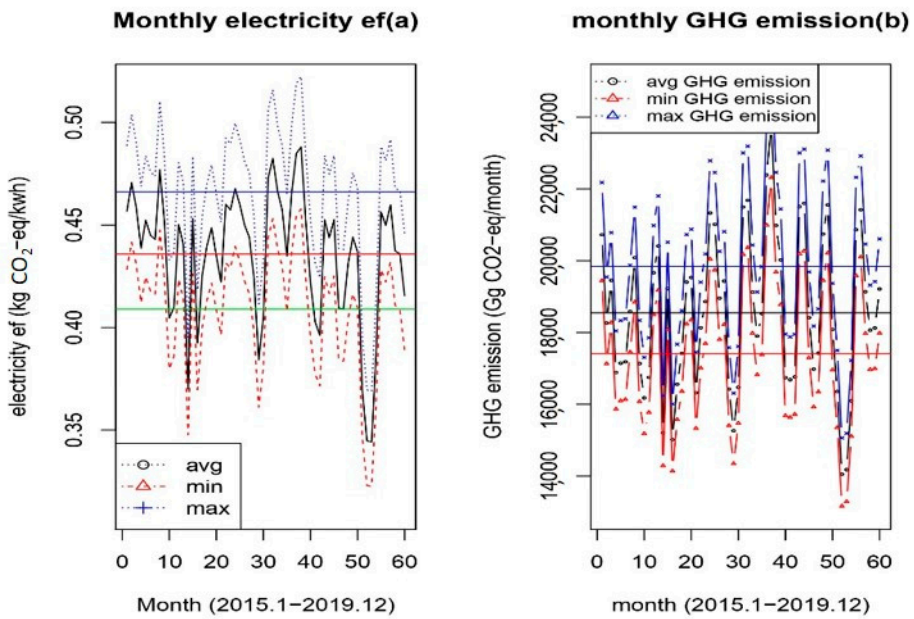

Figure 3. Monthly electricity emission factor (**a**) and monthly GHG emission (**b**).

Causes of the monthly fluctuations of the electricity emission factors may be due to the factors listed below.

(i) The power mix from the fossil fuels, nuclear, and other sources of energy vary continually.
(ii) The transmission loss and in-plant loss (consumption) vary continually.

(iii) The amount and the proportion of the fossil fuels consumed for the fossil fuel power generation vary continually.
(iv) Power plant operating time varies due to repair and maintenance and changing demand for electricity.

Table 2 shows that the overall and five-yearly mean values of the three (average, minimum, and maximum) electricity emission factors are different. Here the overall electricity emission factor is a simple average of the five-yearly electricity emission factors (2015~2019). The coefficient of variations of the average, minimum, and maximum values, 7.38, 7.39, and 7.37%, respectively, are essentially identical. This indicates that differences in the three electricity emission factors originate from the different fuel emission factors, not from the number of data used for computing the electricity emission factor (i.e., 12 vs. 60).

Table 2. The U, mean and RD of the average, minimum, and maximum electricity emission factors.

Year	U (%)			Mean Electricity Emission Factor (kg CO_2-eq/kwh)			RD (%)
	Avg	Min	Max	Avg.	Min	Max	
overall	3.91	4.02	3.93	0.455	0.427	0.487	6.55
2015	8.15	7.91	7.91	0.429	0.403	0.459	6.52
2016	10.37	10.53	9.97	0.439	0.412	0.470	6.56
2017	9.7	10.74	9.59	0.444	0.416	0.473	6.55
2018	8.08	7.83	8.02	0.432	0.406	0.462	6.53
2019	4.96	4.75	4.84	0.436	0.409	0.466	6.57

To verify the difference among the three (average, minimum, and maximum) electricity emission factors statistically, the box plot, the analysis of variance (ANOVA) test, and the Tukey Honest Significance Difference (HSD) test [44] were performed. The box plot shown in Figure 4a supports that there are differences among the three electricity emission factors. The ANOVA test [45], results not shown here, indicates that there is a statistically significant difference among the three. The 95% family-wise confidence level (b) from the HSD test shown in Figure 4b indicates that the three are significantly different.

The U of the three different electricity emission factors shown in Table 2 range from 3.91% to 10.37% (for the average electricity emission factor case) but are essentially the same in a given year. The same U value indicates that it does not change among the three. However, different U among the five different years may be due to the difference in fuel consumption and net power generation in each year. Smaller U of the overall average electricity emission factor was due to the smoothing effect resulting from more data points (60) compared to fewer data points (12) for each of the five-yearly average electricity emission factors. Note that the overall U is not a simple average of the five U values.

Table 3 shows different mean monthly GHG emissions based on the average, minimum, and maximum electricity emission factors. The coefficient of variation of the mean monthly GHG emissions based on the three electricity emission factors were 11.77, 11.76, and 11.78%, respectively, and they are essentially identical. This is the same observation as in the case of the electricity emission factor discussed in Table 2. That is, the difference among the three different GHG emissions originates from the different electricity emission factors, and thus GHG emissions, not from the number of data used for computing GHG emissions (i.e., 12 vs. 60).

To verify the difference among the three (average, minimum, and maximum) GHG emissions statistically, we performed the same analysis as the electricity emission factors case. The box plot supports that there are differences among the three different GHG emissions. The ANOVA test results indicate that there is a statistically significant difference among the three different GHG emissions. The 95% family-wise confidence level from the HSD plot indicates that the three different GHG emissions are significantly different. These are essentially the same observations as discussed in the electricity emission factor case.

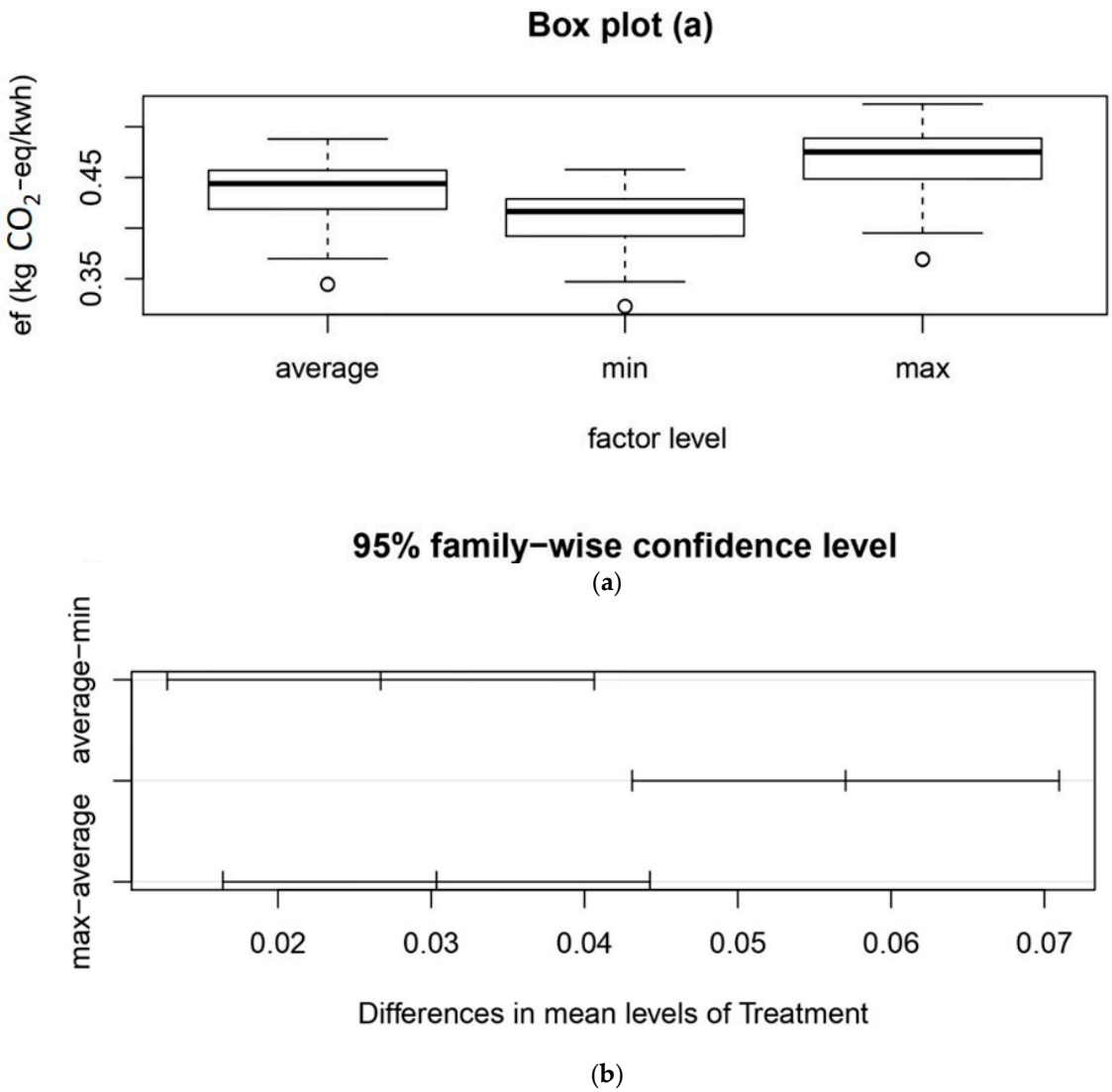

Figure 4. Box plot (**a**) and 95% family-wise confidence level (**b**) Differences in mean levels of Treatment.

Table 3. The U, mean, and RD of the monthly GHG emissions based on the average, minimum, and maximum electricity emission factors.

Year	U (%)			Mean Monthly GHG Emissions (Gg CO_2-eq/Month)			RD (%)
	Avg.	Min	Max	Avg.	Min	Max	
overall	14.04	13.98	14.11	18,507	17,375	19,791	6.55
2015	15.68	15.55	15.75	18,335	17,213	19,609	6.52
2016	14.64	14.67	14.62	18,638	17,494	19,938	6.56
2017	11.79	11.84	11.78	18,988	17,824	20,310	6.55
2018	14.25	14.18	14.31	18,379	17,255	19,656	6.53
2019	9.34	9.35	9.35	18,452	17,318	19,740	6.57

The U of the overall and yearly GHG emissions shown in Table 3 range from 9.34% to 15.75% but are essentially the same in a given year. The same U indicates that it does not change among the three different GHG emissions. However, different U of the three GHG emissions among different years is attributed to the difference in fuel consumption and net power generation in each year.

The RD among the overall and yearly GHG emissions shown in Table 3 are essentially identical, ranging from 6.53% to 6.57%. The same was observed in the electricity emission

factor case. This indicates that there are inherent differences among the average, minimum, and maximum electricity emission factors originating from the differences in the three different fuel emission factors. Thus, choosing the average fuel emission factor over the other two is the cause of uncertainty in the electricity emission factor and GHG emissions.

The U ratio between the GHG U value and the electricity emission factor U value of the three cases shown in Table 4 indicate that there is no difference in the U ratio in a given year. However, there are significant differences among different years, the ratio ranging from 1.22 to 3.63 (in the case of minimum electricity emission factors). Again, this is the same observation as above.

Table 4. The U ratio (GHG U value/electricity emission factor U value).

Year	Average	Minimum	Maximum
overall	3.59	3.63	3.55
2015	1.92	1.93	1.91
2016	1.41	1.42	1.38
2017	1.22	1.22	1.22
2018	1.76	1.75	1.76
2019	1.88	1.85	1.90

Tables 2–4 show that the uncertainties of GHG emissions are higher than those of the electricity emission factors, indicating that the uncertainty of GHG emission propagates. This is because of two different sources of uncertainties involved in computing GHG emission. They are the uncertainty of the electricity emission factor and that of the net power generation. The net power generation has been involved twice in computing GHG emission, once in the electricity emission factor computation, and the other in the GHG emission computation.

Table 5 shows the statistics of the electricity emission factors including the mean, CI and U computed under the proposed and Tier I approach, each with two different scenarios. The proposed approach under the 5-yearly scenario shows approximately two times higher U value compared to that of the 60-monthly scenario. This was expected that the former has only 5 data, while the latter has 60. More data gives smaller variance and thus smaller CI and U compared to the fewer data case. Both scenarios under the proposed approach have the same mean of 0.437 kg CO_2-eq/kwh.

Table 5. The mean, CI, and U of the electricity emission factors for different scenarios.

	Proposed Approach		Tier I Approach	
	5-Yearly	60-Monthly	Single	60-Monthly
Mean (kg CO_2-eq/kwh)	0.437	0.437	0.435	0.435
CI (kg CO_2-eq/kwh)	[0.424, 0.449]	[0.431, 0.443]	-	[0.427, 0.444]
U (%)	5.62	2.56	-	3.82

The two different scenarios under the Tier I approach have the same mean of 0.435 kg CO_2-eq/kwh. A point estimate cannot represent the variability of the data used for computing the electricity emission factor. This indicates that the point estimate may not be used alone. Instead, the CI can be used, for it represents the variability of the data.

The CI and U among the three different scenarios (two under the proposed approach and one under the Tier I approach) are different. The 60-monthly scenario under the proposed approach gives the smallest CI and U. This is because the 60-monthly scenario under the proposed approach considers three different fuel emission factors explicitly. This is in contrast to the use of the average fuel emission factor in the 60-monthly scenario of the Tier I approach.

There is a limited number of research on the uncertainty of the electricity emission factors today. The weak law of large numbers (WLLN) states that the probability of the

absolute difference between the sample mean Mn and the true mean of the sample (a sequence of random variable Xj) approaches 0 for every $\varepsilon > 0$ when n approaches infinity, in accordance with the probability in convergence [46]. Here ε is termed accuracy, and often the value of ε is chosen around 3 percentage points of the absolute difference between Mn and the expected value of X of the sample in most of the statistical inference.

The U defined as the half-width of the CI divided by the mean of the upper and lower bound of the CI can be considered similar to the accuracy ε in WLLN. Hence, the U can be envisaged as the accuracy of the CI. This study reports that the U of the electricity emission factor is 2.56%. The 2.56% accuracy can be a reasonable accuracy.

The electricity emission factor is used for computing GHG emissions from electricity generation and consumption. A prerequisite for an accurate estimation of GHG emissions is the accurate estimation of the electricity emission factor. In this respect, the electricity emission factor should be expressed as an interval estimate, and the CI and U should have the smallest values. In addition, a suitable time period should be chosen, and a large number of data points should be available. Furthermore, different fuel emission factors should also be considered to reflect the variability of the electricity emission factor. This leads to the conclusion that the 60-monthly scenario is the best scenario for computing the electricity emission factor in this study. The CI and mean of the electricity emission factor can then be used to compute GHG emissions from the electricity generation.

In addition to the bootstrap method, there are other simulation methods such as the Monte Carlo Simulation (MCS) method. However, prerequisite of the MCS method is the identification of the probability density function of the raw data, which is the most difficult to estimate accurately such that inaccurate results from the MCS method may arise [21–23,42].

The current GHG emission estimation method by IPCC focuses on the point estimate of the data [34]. The Tier I approach (60-monthly) in Table 5 treated fuel consumption and net power generation as random variables; as such it can address the variability of the input data and can be compared with the proposed approach. Although the mean of GHG emissions in both approaches was the same, the U of the Tier I approach was 1.5 times higher than that of the proposed approach. This indicates that the Tier I approach based on the average fuel emission factors would generate less accurate GHG emission values compared to the proposed approach.

This observation is a piece of assuring evidence that the electricity emission factor must incorporate different fuel emission factors (average, minimum, and maximum), and fuel consumption per net power generation within a time period covered and the number of data used. Furthermore, the propagation of error (uncertainty) from the electricity emission factor to GHG emission indicates that there is a need for future research that minimizes the propagation error. This may suggest that Bayesian inference statistics may need to be applied instead of the classical inference statistics adopted in this study.

The percent contribution of CO_2, CH_4, and N_2O to GHG emission from fossil fuel power generation was also analyzed. The percent contribution of CO_2, CH_4 and N_2O to GHG emission from the fossil fuel power generation showed that most GHG emissions came from CO_2 (>99.5%). Contributions from CH_4 and N_2O were less than 0.05 and 0.44% on average, respectively.

4. Conclusions

Conclusions from this study are:

1. The electricity emission factor can be expressed as a function of the three different (average, minimum, and maximum) fuel emission factors, monthly fuel consumption, and monthly net power generation.
2. The bootstrapped data based on the 60-monthly average, minimum, and maximum electricity emission factors under the proposed approach can be used for computing the mean, CI, and U of the electricity emission factor and GHG emission. The CI, mean,

and U values of the electricity emission factor were (0.431, 0.443) kg CO_2-eq/kwh, 0.437 kg CO_2-eq/kwh and 2.56%, respectively.

3. The uncertainties of GHG emissions are higher than those of the electricity emission factors, indicating that uncertainty of GHG emission propagates.
4. Choosing the average fuel emission factor over the minimum and maximum fuel emission factors is the cause of uncertainty in the electricity emission factor and GHG emissions.

Author Contributions: K.M.L. conceived the research idea, analyzed the results, coded R programs, and drafted manuscript. M.H.L. collected data, processed the data using the coded R program, and contributed to the discussion. Both authors have read and agreed to the published version of the manuscript. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Brander, M.; Sood, A.; Wylie, C.; Haughton, A.; Lovell, J. *Electricity-Specific Emission Factors for Grid Electricity*; Technical Paper; Ecometrica: London, UK, 2011.
2. International Energy Agency. *CO_2 Emissions from Fuel Combustion 2019 Highlights*; International Energy Agency: Paris, France, 2019.
3. Edelenbosch, O.Y.; Kermeli, K.; Crijns-Graus, W.; Worrell, E.; Bibas, R.; Fais, B.; Fujimori, S.; Kyle, P.; Sano, F.; van Vuuren, D.P. Comparing projections of industrial energy demand and greenhouse gas emissions in long-term energy models. *Energy* **2017**, *122*, 701–710. [CrossRef]
4. Olivier, J.G.J.; Schure, K.M.; Peters, J. *Trends in Global CO_2 and Total Greenhouse Gas Emissions*; PBL Netherlands Environmental Assessment Agency: The Hague, The Netherlands, 2017; p. 5.
5. Chuang, J.; Lien, H.-L.; Den, W.; Iskandar, L.; Liao, P.-H. The relationship between electricity emission factor and remodifiedable energy certificate: The free rider and outsider effect. *Sustain. Environ. Res.* **2018**, *28*, 422–429. [CrossRef]
6. Shearer, C.; Fofrich, R.; Davis, S.J. Future CO_2 emissions and electricity generation from proposed coal-fired power plants in India. *Earth's Future* **2017**, *5*, 408–416. [CrossRef]
7. USEIA. How Much Carbon Dioxide Is Produced Per Kilowatthour of U.S. Electricity Generation? Available online: https://www.eia.gov/tools/faqs/faq.php?id=74&t=11#:~{}:text=In2019%2CtotalU.S.electricity,ofCO2emissionsperkWh (accessed on 10 March 2021).
8. Milovanoff, A.; Dandres, T.; Gaudreault, C.; Cheriet, M.; Samson, R. Real-time environmental assessment of electricity use: A tool for sustainable demand-side management programs. *Int. J. Life Cycle Assess.* **2017**, *23*, 1981–1994. [CrossRef]
9. Collinge, W.O.; Rickenbacker, H.J.; Landis, A.E.; Thiel, C.; Bilec, M.M. Dynamic Life Cycle Assessments of a Conventional Green Building and a Net Zero Energy Building: Exploration of Static, Dynamic, Attributional, and Consequential Electricity Grid Models. *Environ. Sci. Technol.* **2018**, *52*, 11429–11438. [CrossRef] [PubMed]
10. Hawkes, A. Long-run marginal CO_2 emissions factors in national electricity systems. *Appl. Energy* **2014**, *125*, 197–205. [CrossRef]
11. Dandres, T.; Moghaddam, R.F.; Nguyen, K.K.; Lemieux, Y.; Samson, R.; Cheriet, M. Consideration of marginal electricity in real-time minimization of distributed data centre emissions. *J. Clean. Prod.* **2017**, *143*, 116–124. [CrossRef]
12. Dandres, T.; Langevin, A.; Walzberg, J.; Abdulnour, L.; Riekstin, A.C.; Margni, M.; Samson, R.; Cheriet, M. Toward a Smarter Electricity Consumption. 2020. Available online: https://emi-ime.ca/wp-content/uploads/2020/02/ETS_POLY_Dandres_Samson_Margni_Near_real-time_modelling_and_smart_management_of_electricity_consumption.pdf (accessed on 14 March 2021).
13. Ekvall, T. Attributional and Consequential Life Cycle Assessment. In *Sustainability Assessment at the 21st Century*; Bastante-Ceca, M.J., Fuentes-Bargues, J.L., Hufnagel, L., Mihai, F.-C., Iatu, C., Eds.; IntechOpen: London, UK, 2019; Available online: https://www.intechopen.com/chapters/69212 (accessed on 20 February 2021). [CrossRef]
14. Kono, J.; Ostermeyer, Y.; Wallbaum, H. The trends of hourly carbon emission factors in Germany and investigation on relevant consumption patterns for its application. *Int. J. Life Cycle Assess.* **2017**, *22*, 1493–1501. [CrossRef]
15. *IEEE Std 1922.2-2019—IEEE Standard for a Method to Calculate Near Real-Time Emissions of Information and Communication Technology Infrastructure*; IEEE Communications Society: New York, NY, USA, 2019.
16. Donat, L.; Schindler, H.; Burck, J. *Climate Transparency Report 2019*; Elsevier: Berlin, Germany, 2019.
17. Spalding-Fecher, R. What is the carbon emission factor for the South African electricity grid? *J. Energy S. Afr.* **2011**, *22*, 8–14. [CrossRef]

18. Song, R.; Zhu, J.; Hou, P.; Wang, H. *Getting Every Ton of Emissions Right: An Analysis of Emission Factors for Purchased Electricity in China*; World Resource Institute: Washington, DC, USA, 2013; p. 16.
19. Park, Y.-S.; Yeon, S.-M.; Lee, G.-Y.; Park, K.-H. Proposed Consecutive Uncertainty Analysis Procedure of the Greenhouse Gas Emission Model Output for Products. *Sustainability* **2019**, *11*, 2712. [CrossRef]
20. Yang, L.; Yu, B.; Yang, B.; Chen, H.; Malima, G.; Wei, Y.-M. Life cycle environmental assessment of electric and internal combustion engine vehicles in China. *J. Clean. Prod.* **2021**, *285*, 124899. [CrossRef]
21. Lee, M.H.; Lee, J.S.; Lee, J.Y.; Kim, Y.H.; Park, Y.S.; Lee, K.M. Uncertainty analysis of a GHG emission model output using the block bootstrap and Monte Carlo simulation. *Sustainability* **2017**, *9*, 1522. [CrossRef]
22. Lee, J.Y.; Lee, M.H.; Lee, J.S.; Chun, Y.-Y.; Kim, K.H.; Kim, M.S.; Lee, K.M. Developing emission factors for dairy cow enteric fermentation in Korea. *J. Clean. Prod.* **2018**, *198*, 754–762. [CrossRef]
23. Lee, J.S.; Lee, M.H.; Chun, Y.-Y.; Lee, K.M. Uncertainty Analysis of the Water Scarcity Footprint Based on the AWARE Model Considering Temporal Variations. *Water* **2018**, *10*, 341. [CrossRef]
24. Kim, M.; Yang, S.-H.; Oh, Y.K.; Park, K.-H. Estimation of greenhouse gas emissions from Korean livestock during the period 1990–2013. *J. Clim. Chang. Res.* **2016**, *7*, 383–390. [CrossRef]
25. Lee, H.J.; Lee, S.C. National methane inventory relevant to livestock enteric fermentation. *J. Anim. Sci. Technol.* **2003**, *45*, 997–1006.
26. Mavromatidis, G.; Orehounig, K.; Carmeliet, J. Uncertainty and global sensitivity analysis for the optimal design of distributed energy systems. *Appl. Energy* **2018**, *214*, 219–238. [CrossRef]
27. Cho, Y. *Yearbook of Energy Statistics*; Enerdata: Ulsan, Korea, 2020; pp. 175–214.
28. *Statistics of Electic Power in Korea*; Enerdata: Ulsan, Korea, 2020; pp. 3–181.
29. Soimakallio, S.; Kiviluoma, J.; Saikku, L. The complexity and challenges of determining GHG (greenhouse gas) emissions from grid electricity consumption and conservation in LCA (life cycle assessment)–a methodological review. *Energy* **2011**, *36*, 6705–6713. [CrossRef]
30. Jin, S.W.; Li, Y.P.; Nie, S.; Sun, J. The potential role of carbon capture and storage technology in sustainable electric-power systems under multiple uncertainties. *Remodified. Sustain. Energy Rev.* **2017**, *80*, 467–480. [CrossRef]
31. Ilyas, H.M.A.; Safa, M.; Bailey, A.; Rauf, S.; Pangborn, M. The carbon footprint of energy consumption in pastoral and barn dairy farming systems: A case study from Canterbury, Modified Zealand. *Sustainability* **2019**, *11*, 4809. [CrossRef]
32. Lemay, L.; Reddy, K.; Randolph, D.; Shah, A. Mitigating and Adapting to Climate Change. In *Engineering for Sustainable Communities: Principles and Practices*; ASCE (American Society of Civil Engineers): Reston, VA, USA, 2017; pp. 283–305.
33. Martins, F.; Felgueiras, C.; Smitková, M. Fossil fuel energy consumption in European countries. *Energy Procedia* **2018**, *153*, 107–111. [CrossRef]
34. Shin, H.; Kim, T.H.; Kim, H.; Lee, S.; Kim, W. Environmental shutdown of coal-fired generators for greenhouse gas reduction: A case study of South Korea. *Appl. Energy* **2019**, *252*, 113453. [CrossRef]
35. Gómez, D.R.; Watterson, J.D.; Americano, B.B.; Ha, C.; Marland, G.; Matsika, E.; Namayanga, L.N.; Osman-Elasha, B.; Kalenga Saka, J.D.; Treanton, K. *Intergovernmental Panel on Climate Change (IPCC) Guidelines for National Greenhouse Gas Inventories*; Volume 2: Energy, Stationary Combustion; Institute for Global Environmental Strategies: Kanagawa, Japan, 2006.
36. Frey, C.; Penman, J.; Hanle, L.; Monni, S.; Ogle, S. *Guidelines for National Greenhouse Gas Inventories Chapter 3: Uncertainties*; Intergovernmental Panel on Climate Change (IPCC): Hayama, Japan, 2006.
37. Orloff, J.; Bloom, J. Bootstrap Confidence Intervals Class 24. Available online: https://ocw.mit.edu/courses/mathematics/18-05-introduction-to-probability-and-statistics-spring-2014/ (accessed on 1 March 2021).
38. Kabacoff, R.I. R in Action: Data Analysis and Graphics with R. Manning: Shelter Island, NY, USA, 2011.
39. UCLA Institute for Digital Research and Education. How Can I Generate Bootstrap Statistics in R. Available online: https://stats.idre.ucla.edu/r/faq/how-can-i-generate-bootstrap-statistics-in-r/ (accessed on 10 March 2021).
40. DiCiccio, T.J.; Efron, B. Bootstrap confidence intervals. *Stat. Sci.* **1996**, 189–212.
41. Tong, L.-I.; Saminathan, R.; Chang, C.W. Uncertainty assessment of non-normal emission estimates using non-parametric bootstrap confidence intervals. *J. Environ. Inform.* **2016**, *28*, 61–70. [CrossRef]
42. Lee, K.M.; Lee, M.H.; Lee, J.S.; Lee, J.Y. Uncertainty Analysis of Greenhouse Gas (GHG) Emissions Simulated by the Parametric Monte Carlo Simulation and Nonparametric Bootstrap Method. *Energies* **2020**, *13*, 4965. [CrossRef]
43. De Jong, S.; Antonissen, K.; Hoefnagels, R.; Lonza, L.; Wang, M.; Faaij, A.; Junginger, M. Life-cycle analysis of greenhouse gas emissions from remodifiedable jet fuel production. *Biotechnol. Biofuels* **2017**, *10*, 1–18. [CrossRef]
44. Abdi, H.; Williams, L.J. Tukey's honestly significant difference (HSD) test. *Encycl. Res. Des.* **2010**, *3*, 1–5.
45. Kim, T.K. Understanding one-way ANOVA using conceptual figures. *Korean J. Anesthesiol.* **2017**, *70*, 22. [CrossRef]
46. Bertsekas, D.P.; Tsitsiklis, J.N. *Introduction to Probability*, 2nd ed.; Athena Scientific: Nashua, NH, USA, 2008.