Working Paper

Statistical Analysis of Investment Costs for Power Generation Technologies

Manfred Strubegger and Irina Reitgruber

WP-95-109
November 1995

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1. Introduction

Differences in the base assumptions and input data, more often than not, are the fundamental reason explaining the different results of energy models. This paper analyzes variations in investment cost data for electricity generation plants as found in different data sources ([1] to [7]).

The analysis was carried out for the following ten types of power generating technologies:

— coal power plants,

— coal gasification combined cycle plants,

— gas turbines,

— gas combined cycle plants,

— nuclear power plants,

— biomass and wood power plants,

— solar thermal power plants,

— photovoltaic power plants,

— wind power plants, and

— geothermal power plants.

First we present a straight forward statistical analysis of the collected investment cost data by applyig the method of least sqares on each type of powerplant individually. Then these samples are further subdivided into data groups for industrialized and developing countries. For the industrialized countries it was possible to further disaggregate the data into data sets with estimates for existing and future technologies.

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In a second step the resulting cost ranges are used as input to an energy model to show the variation in the results of that specific model, when the investment costs are varied within the suggested ranges from the first step.

2. Tools used

The data and results shown in this analysis are mainly based on two instruments:

— the CO_2 mitigation technology data base (CO2DB [8]):
Developed to collect data for technologies relevant for mitigating CO_2 emissions, CO_2 can be used more generally to collect and analyze data for a wide range of energy technologies. Currently the data base contains some 1700 technologies, ranging from resource extraction technologies to end use devices with their economic, technical and ecological data. The CO2DB served as data base for the investment costs of electricity generation technologies investigated in this analysis.

— the Model for Energy Supply Systems and their General Environmental Impact (MESSAGE [9]):
An optimization model for comparing various technologies with respect to their fitness in the complete energy chain, taking into account their economic, technical and ecological parameters. MESSAGE was used to analyze the effect of different investment cost estimates on the power generation systems. As an exemplary model, the global energy model used for the joint IIASA and WEC study [10], consisting of 11 interlinked world regions with a time horizon of up to 2100 was used in this analysis.

3. Collected Data

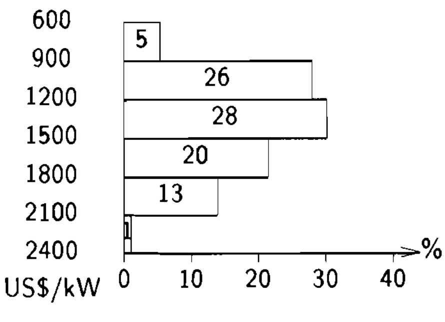
The data of the CO2DB stem from various sources. To minimize statistical errors the data origin was traced and data derived from the same original source were taken into account only once. Table 1 shows the sample size as well as the minimum and maximum values of the specific investment costs for each of the technologies analyzed.

Table 1. Investment cost ranges [US$'90/kW] and sample sizes of 10 types of technologies

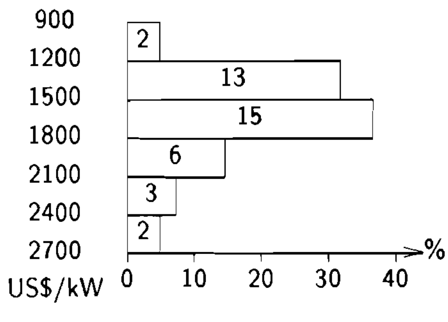
technology	short name	total sample size	minimum value	maximum value
coal power plant	cppl	93	607	2122
coal combined cycles	ccc	41	995	2600
gas turbines	gtu	26	174	1201
gas combined cycle	gcc	26	448	1735
nuclear power plant	nuc	39	1004	3447
biomass power plant	bio	45	652	3752
solar thermal power plant	sth	100	867	6129
solar photovoltaics	spv	68	640	36907
wind power plant	wind	54	705	11482
geothermal power plant	geo	111	474	8997
total number of estimates		603		

The following graphs show the distribution of the original data as histograms with the investment costs on the vertical axis and the percentage of estimates falling into a specific cost range on the horizontal axis. The figures inside the boxes show the number of estimates in each cost category, the headings contain the total number of estimates.

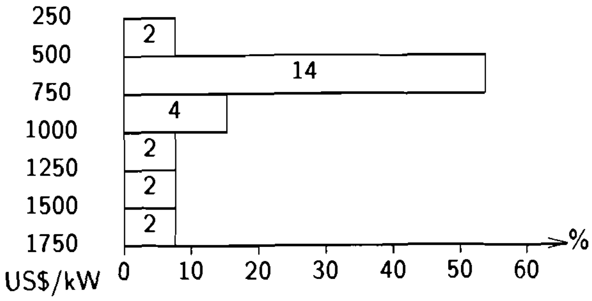
Coal power plants (93)



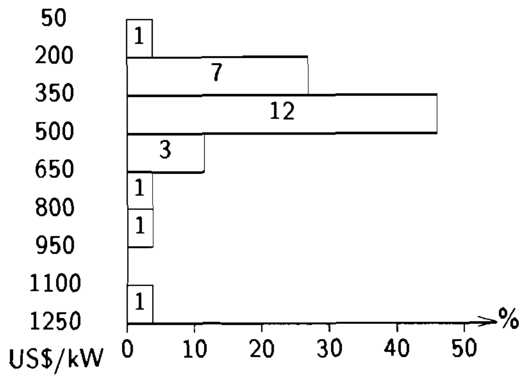
Coal combined cycles (41)



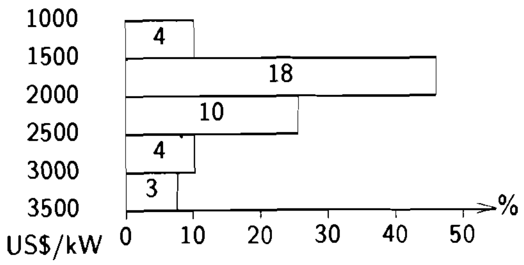
Gas combined cycles (26)



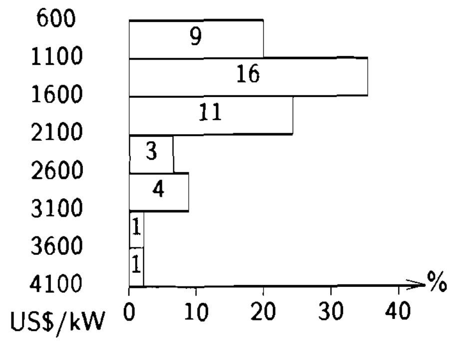
Gas turbines (26)



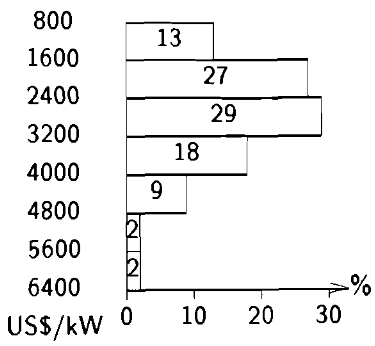
Nuclear power plants (39)



Biomass power plants (45)



Solar thermal (100)



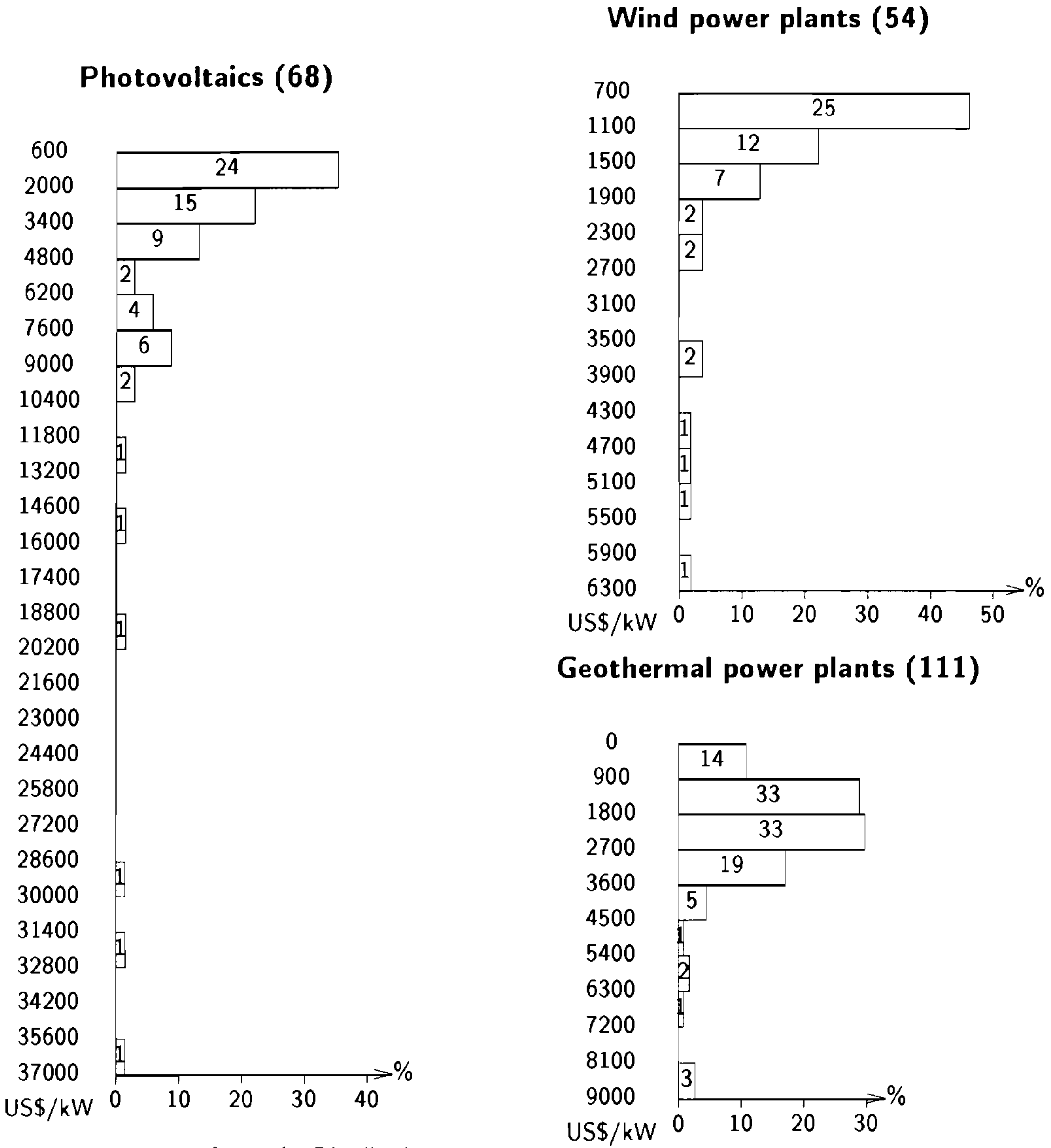


Figure 1. Distribution of original estimates to cost categories

All cost distributions show a more or less pronounced tail towards the higher cost ranges. These tails, which cannot be explained by the analysis, seem to reflect three facts:

— maturity of the technology,

— scalability, and

— site dependence.

Technologies producing electricity from renewables show the longest tails, as these systems are in their early development stages and are very site dependent. For the two technologies with the longest tails (photovoltaics[1] and wind), scalability — they can be built from very small to fairly large units — expands the cost range into the higher categories (very small units are more expensive per kW installed capacity). Additionally, different accounting schemes may contribute to the shape of the distribution: The sources do not always state explicitly, if the given power is peak or average power, which of course results in drastically different cost estimates. The majority of the estimates, however, refer to peak capacity.

In an initial step, the mean and the standard deviation was estimated for each type of powerplant individually. Table 2 shows the sample means and sample standard deviations for each type of power plant:

Table 2. Sample means and standard deviations [US$'90/kW]

Technology	Sample size	sample mean	mean - std deviation	mean + std deviation
cppl	93	1392	1065	1719
ccc	41	1667	1312	2022
gtu	26	464	251	677
gcc	26	820	460	1180
nuc	39	2057	1497	2617
bio	45	1658	973	2343
sth	100	2754	1673	3835
spv*)	62	3512	961	6063
wind	54	1717	34	3400
geo	111	2325	754	3896

*) Six observations with cost estimates above 11800 US$/kW were excluded from the sample

Figure 2 shows the means and standard deviations for each group of power plants, ordered by increasing mean costs, and again depicts the conclusions drawn from the histograms, the newer and the more site dependent a technology, the larger the standard deviation.

1. *The highest three estimates refer to a solar installation driving a small water pump in Mali and were not considered any further, as they cannot be compared to general power generation units. The next three estimates are old estimates from the seventies and were also excluded as they certainly do not reflect today's status.*

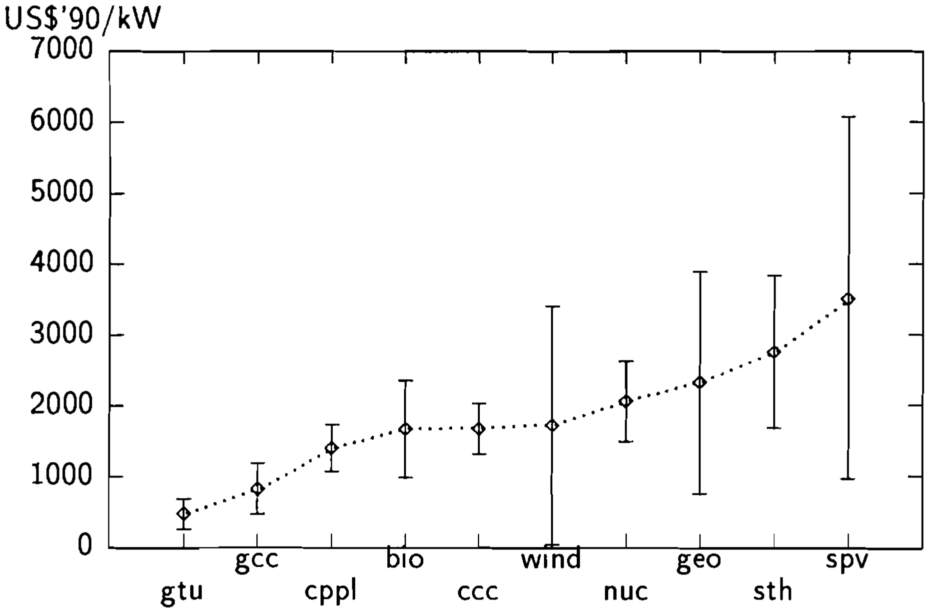


Figure 2. Mean investment costs and standard deviations of original estimates

Figure 2 also shows, that a simple regression can not yield satisfactory results for giving realistic cost ranges for further model analysis. In many cases the compiled cost ranges show unrealistically low figures, reaching less than 50. US$/kW for wind power plants. In contrast, the lowest original estimate for wind power plants is 704 US$/kW. This is the result of a method which assumes a normal distribution of the data. The data analyzed here do certainly not fulfill this criterion.

In order to obtain more realistic results an econometric model based on the complete data set was built and estimated. This model and its results are described in the next sections.

4. An econometric model for the analysis of investment costs

To utilize the information contained in CO2DB, a two-step approach was taken to derive plausible cost estimates with reasonable deviations from a mean value:

1. taking into consideration that the data chosen for this analysis stem from 18 data sources, it was statistically tested if a bias towards higher or lower estimates could be detected for individual data sources,

2. after correcting for potential biases, the analysis focused on trends related to the geographical location of the power plants, as well as to the time period for which the estimates were made.

4.1 Analysis of the data sources

All the data analyzed come from 18 sources. While many of these sources provide investment cost estimates for only a few electricity generation technologies, some of them give the estimates for almost all 10 technologies. To estimate possible biases, the data sources giving estimates for at least 6 different technologies were chosen (these are items [1]-[7] in the list of references). Thus we divided the data into 8 groups: while groups 1 to 7 consist of the data coming from literature sources [1]-[7] correspondingly, the last group contains the rest of the data. The following econometric model was used for trend estimation:

$$I = \sum_{i=1}^{10} t_i D_i + \sum_{i=1}^{8} l_i L_i + \epsilon$$

Equation 1. Regression formula for data sources analysis

where:

I	investment costs
D_i, $i=1,...10$	0-1 variables for each of the ten technologies
L_i, $i=1,...7$	0-1 variables for the seven complete data sources
L_8	dummy variable for the remaining technologies
t_i, l_i	regression coefficients
ϵ	error term

Almost all parameters associated with data sources [1] to [7] turned out to be statistically insignificant (all corresponding t-statistics were below 2). An exception is the Report of Stuttgart University [3] which provides cost estimates slightly below the average with a corresponding t-ratio on the border of being significant (2.5). However, this can not seriously influence further statistical analysis of the data, because only a small sample of data comes from this source (one cost estimate for each technology). Therefore we can conclude that the main data sources, though providing a large variety of diverging cost estimates, have no significant bias and can be used without corrections for further statistical analysis of the data.

4.2 Analysis of the investment data

To provide a plausible estimate of the investment costs, statistical modeling can be used to find factors influencing the costs in general (independent of technology) and to give quantitative estimates of this influence for each of the technologies under consideration.

For this analysis the following two criteria were chosen:

— world region and

— time period for which an estimate was suggested.

To ensure that enough data for statistical modeling remain in each group, we disaggregated into two regional groups:

— industrialized and

— developing countries.

Concerning time periods the data were, for the same reason, also divided into two groups, where the group 'present' involves all the estimates made for years up to 1995 and the group 'future' involves cost forecasts for all future years. Since the future cost estimates concern usually only developed countries, all data fall into three groups: present estimates for industrialized countries (ind), for developing countries (dev) and estimates for future costs in industrialized countries (fut). The size of these subsamples for each technology is shown in Table 3.

Table 3. Technology subgroups and their sample size

technology	short name	total sample size	industrialized present	industrialized future	developing present
coal power plant	cppl	93	62	10	21
coal combined cycles	ccc	41	30	3	8
gas turbines	gtu	26	12	5	9
gas combined cycle	gcc	26	11	5	10
nuclear power plant	nuc	39	21	10	8
biomass power plant	bio	45	31	0	14
solar thermal power plant	sth	100	76	24	0
solar photovoltaics	spv	62	34	29	0
wind power plant	wind	54	28	22	4
geothermal power plant	geo	111	55	28	28
total number of estimates		597	360	135	102

It seems economically plausible to express the deviations in costs associated with developing countries or with future forecasts as percent differences to the present cost estimates for the industrialized countries. Therefore all costs were transformed into logarithms in order to have an additive regression model. Moreover, transforming the data to a logarithmic scale yields data sets conforming closer to a normal distribution, which allows statistical analysis with general methods. Setting up the regression model for logarithmized costs includes the following three steps:

— preliminary analysis of the data distribution to choose the model specification,

— estimation of the model and

— testing the residuals for independence (i.e. whether the model was correctly specified) and for normality (i.e. whether the assumption of a logarithmic distribution is valid).

4.3 Preliminary analysis of the logarithmized data

For the preliminary analysis of the logarithmized data, sample means and variances were computed for each data group and for each technology individually. The corresponding diagrams are shown in Figure 3.

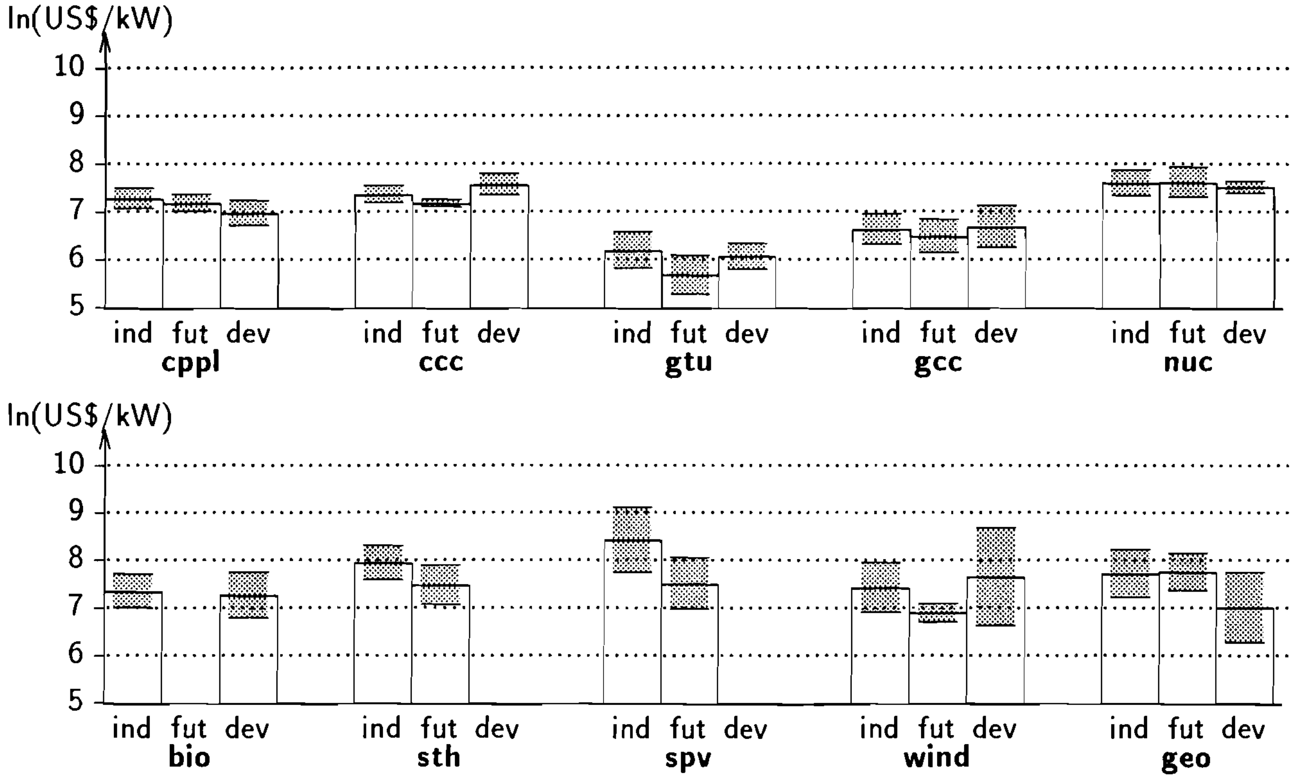


Figure 3. Means and standard deviation in ln(US$'90/kW)

A brief view of the diagrams shows that the estimates for the developing countries exhibit somewhat lower means and higher variances than the ones for the industrialized countries. The three exceptions where the estimates for developing countries show somewhat higher values (coal combined cycles, gas combined cycles, and wind power plants), are, at least for a general conclusion, not plausible. While it may be possible that initial projects in developing countries may be more expensive due to the necessity to buy technology and knowledge from industrialized countries, we see no reason why in the longer run the cost pattern should not follow that of the other technologies. A technology that calls for special attention are the geothermal power plants (the average for the developing countries subsample is significantly lower than the one for the industrial group).

Concerning the projections, the diagrams show, that the means for future estimates are generally somewhat lower than the ones for present estimates with possible exceptions of nuclear and geothermal technologies (where they are somewhat higher) and photovoltaics (where they are essentially lower). These three groups also receive specific variables in the model.

Summarizing the discussions above, we suggest the following model for the investment cost analysis:

$$\ln(I) = \sum_{i=1}^{10} a_i D_i + bD_{dev} + cD_{fut} + \sum_{i \in 5,8,10} d_i (D_i \times D_{fut}) + e_{10}(D_{10} \times D_{dev}) + \epsilon$$

Equation 2. Regression formula for data analysis

where

I	investment costs
D_i, $i=1,...10$	0-1 variables for each of the ten technologies
D_{dev}	0-1 variables indicating developing countries
D_{fut}	0-1 variables indicating estimates or future technologies
a_i, b, c, d_i, e_i	regression coefficients
ϵ	error term

The model reflects the fact that each investment cost estimate contains a component specific for the technology and a component specific for the data group (ind, dev or future). In addition, some technologies and data groups, for which the preliminary analysis showed that they do not follow the general trends, have a specific component (product of the corresponding 0-1 variables). The regression coefficients of these products indicate how much this particular group differs from the general trends.

4.4 Model estimation

The estimation of the model consists of two steps. First, it was estimated with the ordinary least square (OLS) method and the sample variances of residuals for each subsample were computed. The estimated variances vary dramatically with the subsample: from 0.017 for nuclear power in industrialized countries to 1.4 for wind power in developing countries. The data obviously exhibit heteroscedastic behavior and the model was then reestimated with the generalized least square (GLS) method.

At the second step (GLS) all the equations of the model are weighted according to the estimated standard deviations of the residuals of the corresponding subsamples. This leads to the effect, that subsamples with higher standard deviations contribute less to the parameters than subsamples with smaller standard deviations. The adjusted squared R statistics increase from 0.6 for the OLS step to 0.925 for the GLS step. The following table gives the estimated values of the parameters, their standard deviations and t-statistics.

Table 4. Estimated model parameters (GLS)

Parameter		Value	Std. error	t-statistics	normalized
a_1	cppl_ind	7.28	0.027	271.587	1451
a_2	ccc_ind	7.41	0.035	212.264	1652
a_3	gtu_ind	6.19	0.078	79.750	488
a_4	gcc_ind	6.72	0.081	83.017	829
a_5	nuc_ind	7.61	0.029	261.432	2018
a_6	bio_ind	7.37	0.061	120.678	1588
a_7	sth_ind	7.92	0.040	195.809	2752
a_8	spv_ind	8.32	0.128	64.934	4105
a_9	wind_ind	7.27	0.062	118.090	1437
a_{10}	geo_ind	7.73	0.070	110.701	2276
b	dev	−0.136	0.050	−2.728	−13%
c	fut	−0.335	0.053	−6.339	−28%
d_5	nuc_fut	0.121	0.045	2.652	+13%
d_8	spv_fut	−0.255	0.093	−2.703	−23%
d_{10}	geo_fut	0.147	0.047	3.111	+16%
e_{10}	geo_dev	−0.427	0.126	−3.412	−35%

The last column in table 4 shows the normalized values for the estimated parameters. The first ten values of this column directly give the estimated costs for industrialized countries in US$'90/kW for all power plants included in this analysis. The following two values indicate the percentage cost differential for developing countries and future estimates, respectively. The last four values show the percentage cost differentials for the power plants treated specifically, and have to be interpreted as percentage difference on top of the difference shown for parameters b and c, respectively. Thus, e.g.:, future photovoltaics are some 45% (i.e.: $(1-(1-.28)\times(1-.23))\times 100.)$[2] cheaper than present technology.

According to the t-statistics all parameters are significant, so we proceed with the test.

4.5 Testing the residuals

The GLS residuals were tested for independence and normality. With testing for independence, we mean the test showing if for some of the subsamples linear dependencies are left in the residuals (that is certainly not a general test for independence). In other words we test the model (equation 2) against a model where each subsample has its own trend. We build the following regression model for the

2. see the last column of table 4

residuals:

$$\hat{\epsilon} = \sum_{i=1}^{10} s_i D_i + \sum_{i=1}^{10} g_i (D_i \times D_{fut}) + \sum_{i=1}^{10} f_i (D_i \times D_{dev}) + \gamma$$

Equation 3. Regression model for residuals

The result of this regression shows that none of the estimated parameters s, g and f is significant (all t-statistics are below 2.1). Therefore the suggested model from equation 2 is correctly specified. The residuals were tested also for normality with the Kolmogorov-Smirnov [9,10] test. The test results (see table 5) show, that the normality hypothesis can be accepted.

Table 5. Results from Kolmogorov-Smirnov test

sample size:	597
KS statistics:	0.03
KS probability:	0.65

4.6 Conclusions to model estimation

The fact that the suggested model proved to be statistically reasonable (the residuals can be considered independent and normally distributed) allows for the following conclusions.

1. The model provides better quality of estimates for the suggested costs than the results obtained by straight forward analysis of the data. Table 6 gives a comparison of the standard deviation of means for each group, computed from the model and the corresponding subsamples. The estimates for industrialized countries have similar values, whereas for developing countries and for future costs the standard deviations resulting from the model are essentially smaller. The model gives also a possibility of estimating the costs (and standard deviations) for groups were no data are available (future biomass power plants and solar thermal and solar photovoltaic power plants in developing countries). The values of the means computed from the original estimates and from the model are given in table 7.

Table 6. Standard deviation of mean: model estimates and sample values

Technology	stdd(mean), ind		stdd(mean), future		stdd(mean), dev	
	model	sample	model	sample	model	sample
cppl	0.027	0.027	0.056*)	0.109	0.050	0.068
ccc	0.035	0.036	0.059	0.083	0.058	0.123
gtu	0.078	0.115	0.089	0.209	0.077	0.096
gcc	0.081	0.102	0.091	0.190	0.087	0.145
nuc	0.029	0.029	0.056	0.110	0.056	0.132
bio	0.061	0.064	0.080	–	0.073	0.134
sth	0.040	0.042	0.058	0.087	0.063	–
spv	0.128	0.118	0.158	0.098	0.137	–
wind	0.062	0.101	0.044	0.045	0.077	0.591
geo	0.070	0.067	0.061	0.076	0.110	0.140

*) calculated from: $e^2_{cppl}+2\times e_{cppl}\times e_{fut}*c_{fut,cppl}+e^2_{fut}$; with **e** being the standard error (table 4) and **c** the corresponding coefficient from the correlation matrix of regression coefficients.

Table 7. Mean: model estimates and sample values

Technology	mean, ind		mean, future		mean, dev	
	model	sample	model	sample	model	sample
cppl	7.277	7.286	6.942	7.201	7.141	6.983
ccc	7.408	7.372	7.073	7.185	7.272	7.322
gtu	6.182	6.201	5.847	5.682	6.046	6.068
gcc	6.720	6.637	6.385	6.490	6.584	6.692
nuc	7.609	7.607	7.396	7.624	7.473	7.524
bio	7.369	7.359	7.034	–	7.233	7.277
sth	7.925	7.948	7.590	7.491	7.789	–
spv	8.322	8.438	7.732	7.521	8.186	–
wind	7.277	7.430	6.942	6.909	7.141	7.659
geo	7.733	7.733	7.545	7.763	7.170	7.023

2. The analysis proved that the logarithms of the investment costs are normally distributed (with means and variances different for each of the subgroups). This allows to estimate not only means, but also confidence intervals for the means. These intervals give reasonable lower and upper bounds for the suggested cost estimates. To compute these statistics for investment costs directly is difficult, because of the complex distribution of the investment costs (they are exponents of normally distributed random variables). Therefore we compute the statistics for logarithmized costs and then transform the intervals. Table 8 shows values for means and means +/$-$ standard deviation transformed into investment costs (in US$'90/kW). The figures in table 8 compare to the ones shown in table 2 for the initial analysis.

Table 8. Investment costs: mean and mean +/− standard deviation [US$'90/kW]

Technology	ind			future(ind)			dev		
	mean	mean− stddev	mean+ stddev	mean	mean− stddev	mean+ stddev	mean	mean− stddev	mean+ stddev
cppl	1447	1408	1486	1035	978	1094	1263	1201	1327
ccc	1649	1592	1708	1180	1112	1251	1439	1358	1525
gtu	484	448	523	346	317	378	422	391	456
gcc	829	764	899	593	541	649	723	663	789
nuc	2016	1959	2076	1629	1541	1723	1760	1664	1861
bio	1586	1492	1686	1135	1047	1229	1384	1287	1489
sth	2766	2657	2878	1978	1867	2096	2414	2267	2571
spv	4113	3619	4675	2280	1947	2670	3590	3131	4117
wind	1447	1360	1539	1035	990	1081	1263	1169	1364
geo	2282	2128	2448	1891	1779	2010	1300	1164	1451

Table 9 shows the values calculated for a 95% confidence interval (from min to max). These are finally the cost ranges suggested for use in mathematical energy models investigating the competitiveness of power plants in the global electricity market.

Table 9. Investment costs: 95% confidence intervals for means [US$'90/kW]

Technology	ind			future(ind)			dev		
	mean	min	max	mean	min	max	mean	min	max
cppl	1447	1372	1525	1035	927	1155	1263	1145	1393
ccc	1649	1540	1766	1180	1051	1324	1439	1285	1613
gtu	484	415	564	346	291	412	422	363	491
gcc	829	707	971	593	496	709	723	610	858
nuc	2016	1905	2134	1629	1460	1818	1760	1577	1964
bio	1586	1407	1787	1135	970	1327	1384	1200	1597
sth	2766	2557	2991	1978	1766	2216	2414	2134	2731
spv	4113	3201	5286	2280	1673	3108	3590	2745	4696
wind	1447	1281	1634	1035	949	1128	1263	1086	1468
geo	2282	1990	2618	1891	1678	2131	1300	1048	1613

3. There are general trends associated with the cost estimates for the future and for developing countries. Namely, in developing countries the costs are about 13% lower than in the industrialized countries. The only important exception are geothermal power plants, where this estimate is 43% lower. It only can be guessed, that this significantly lower estimate is based on different geological conditions in developing countries as compared to industrialized countries.

   The future costs in industrialized countries are approximately 28% lower than the present ones for most of the technologies. For geothermal power plants the future drop in costs is expected to be around 17% only (probably due to the fact that these costs depend on the geographic location and natural conditions, and that the cheapest locations will no longer be available in the future). For nuclear power plants the relatively small decrease in future costs (19%) can be associated to increasing safety requirements, which lead to cost increases. Fast progress is expected for photovoltaics: about 45% decrease in costs, which can be attributed to technological progress and mass production due to increased utilization of this technology.

Figure 4 summarizes these findings. It is interesting to compare this figure to figure 2, as this clearly shows the improved quality of the model results compared to a standard regression on the original data set:

1. Due to the analysis of the data in an integrated model, it was possible to calculate general trends for the different country and time horizon groups.
2. The results allow the transfer of these trends to similar power generation technologies, not included in this analysis (e.g.: conventional gas power plants, for which not a large enough data set was available, can most likely be treated similar to the fossil power plants investigated).
3. The range of values covered by the standard deviation could be reduced considerably.
4. The results reflect the fact, that the original data show a higher spread towards higher cost categories.

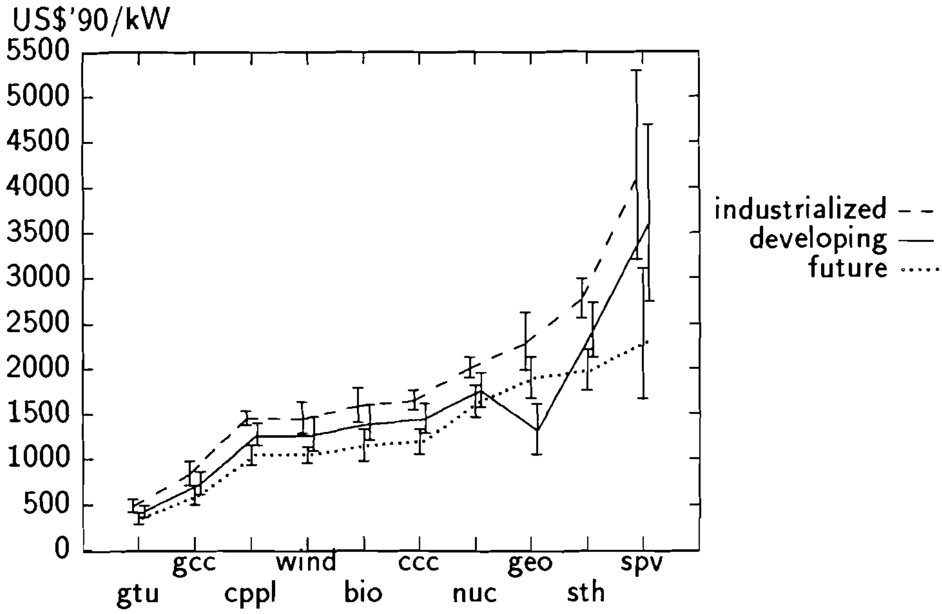


Figure 4. Investment costs with standard deviations from model results

5. Applications of the estimated investment costs

The influence of the estimated investment costs of power generating technologies on the global electricity supply structure was studied by applying the estimated figures from this study to the global version of the MESSAGE energy supply model.

To test the influence of parameter changes, a standard version of the model was taken, together with all its input data for other technologies, such as energy extraction plants and equipment, energy conversion, transport/distribution, and end-use technologies, remaining in place. Based on this setup two test change cases were produced:

1. a test with the initial overall estimates from table 2, and
2. a test with the disaggregated estimates from table 9.

For the second test, the estimated parameters were adapted to reflect possible development paths:
First, the investment costs for the 10 technologies were adopted to the estimated mean values for industrialized and developing countries. For the dynamics of the investment costs, it was assumed, that for industrialized countries the costs decrease exponentially up to the year 2020, so that in 2020 they achieve the target resulting from the statistical model. For most technologies the reduction is 28%, for nuclear, geothermal and photovoltaics it reaches 19%, 17% and 45% respectively. After 2020 the decrease in costs for mature technologies (coal, gas, low cost nuclear) is supposed to stop due to absence of further technological improvements in this field, whereas for new technologies (solar, geo, bio, wind, high cost nuclear) the costs will further experience a decline, though at a lower rate.

For the developing countries, the following cost dynamics was assumed: for mature technologies the costs approach those estimated for the year 2040 in the industrialized countries. Afterwards they follow the same path as the costs for industrialized countries now. This reflects the fact, that the lower estimates for developing countries are based on less costly technologies with lower environmental standards. Establishing better environmental standards increases the cost of power generation equipment, which offsets cost decreases initially, only when current standards are met, the investment costs can pick up decreases due to technological progress. For new technologies the cost dynamics in developing countries was assumed to be the same as in industrialized countries, assuming, that technological progress is transferred to the developing countries. However, as with mature technologies, the final price is the one for the future in industrialized countries, i.e.: the cost differential disappears.

The Reforming Countries are treated the same as industrialized countries.

The following figures show the results for electricity generation by technology for the two change cases. The graphic on the left hand always shows the development with constant investment costs, the one at the right hand side the development with decreasing investment costs.

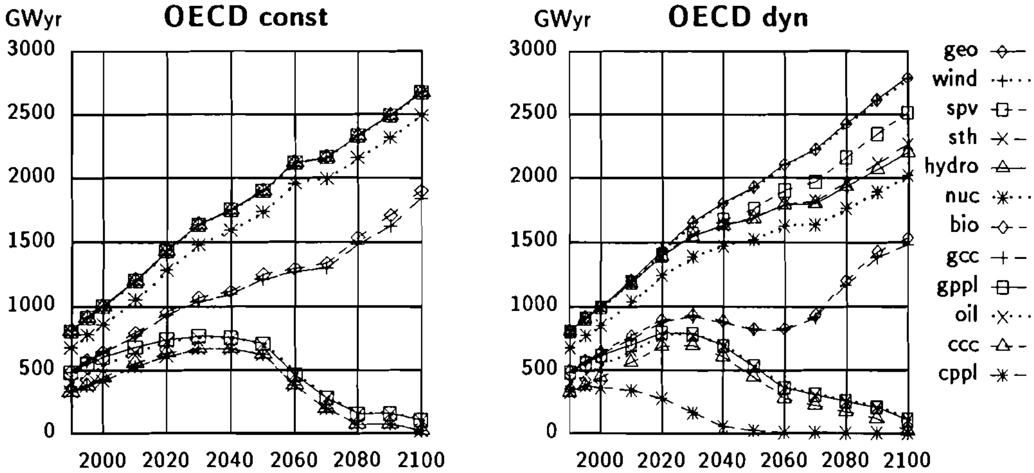


Figure 5. Electricity production in industrialized countries without (left) and with (right) changing investment costs [GWyr]

The comparison for the industrialized countries shows, that, starting around 2020, the cost changes favour the systems using renewable energy forms (curves towards the top of the graph). This is, of course, no big surprise, as these systems are at the beginning of their life cycle and thus will profit from sharper cost decreases than todays mature technologies. By the end of the time horizon, the electricity output of these systems double compared to the case with no price changes. When examining the fossil technologies (curves at the lower end of the graph), one sees, that advanced coal systems (like combined cycles) can replace the conventional coal power plants by the middle of next century. In both tests the bulk production comes from natural gas converted in gas combined cycles.

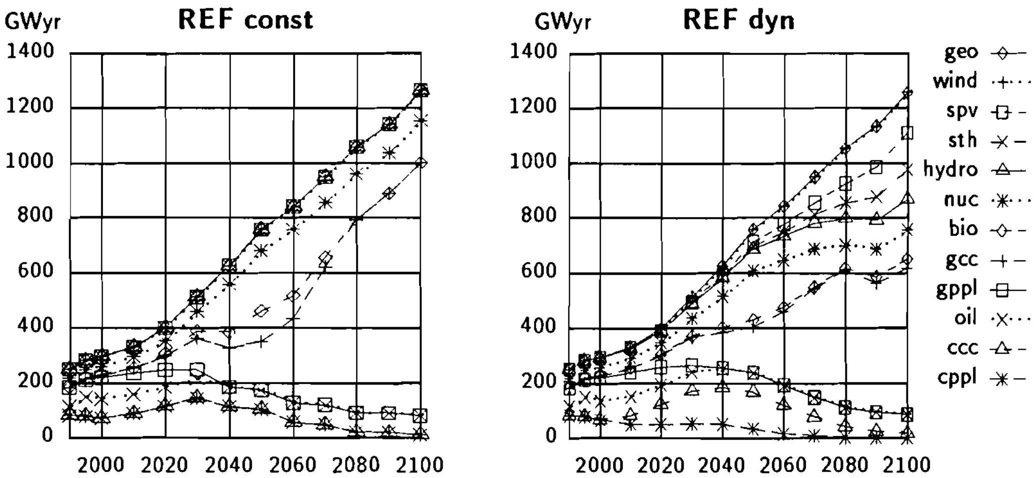


Figure 6. Electricity production in reforming countries without (left) and with (right) changing investment costs [GWyr]

The picture for the reforming countries reveals a similar structure as the one for the industrialized countries. The difference being, that the share of natural gas in the supply menu is reduced in favour to the higher production from environmentally more benign ways to generate electricity.

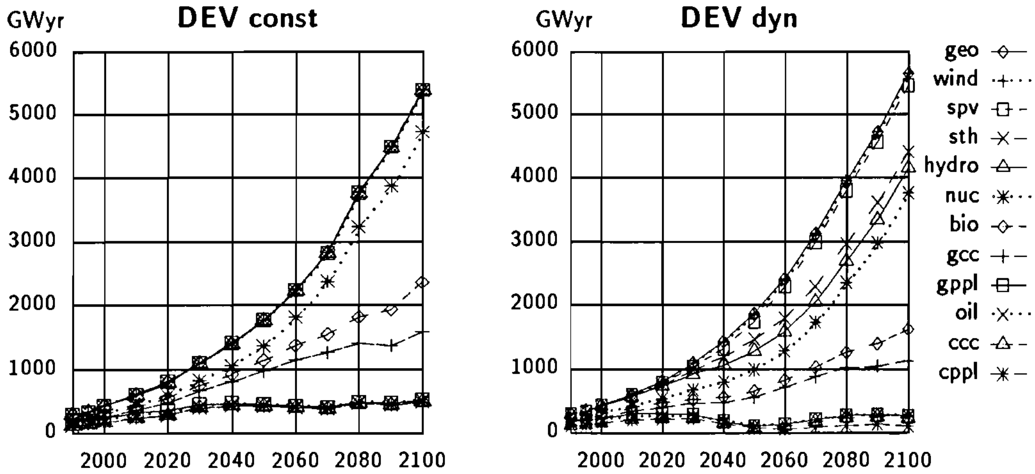


Figure 7. Electricity production in developing countries without (left) and with (right) changing investment costs [GWyr]

In the developing countries, only production from coal is somewhat reduced due to the shifts in production costs. The overall production structure hardly changes, as the developing countries have hardly any degrees of freedom. Being mostly supply constrained and being faced with a rapidly increasing demand all energy carriers have to be utilized close to their potential. Moreover, the cost changes are smaller, than in the industrialized countries, as the cost decreases are partially offset by the need to install cleaner power plants with higher costs than so far.

Summarizing, it can be said, that the price changes for electricity production equipment leads to a more balanced production pattern in all three regions and increases the potential to produce more electricity from sources with strongly reduced CO_2 emissions.

Summarizing, these differences between the two test cases is shown in figure 8, where electricity production is aggregated into the primary energy categories fossil, nuclear and renewable. Here one can see clearly, that the share of electricity generated from renewable sources nearly doubles, if the estimated investment cost figures are used rather than constant values over the complete time horizon.

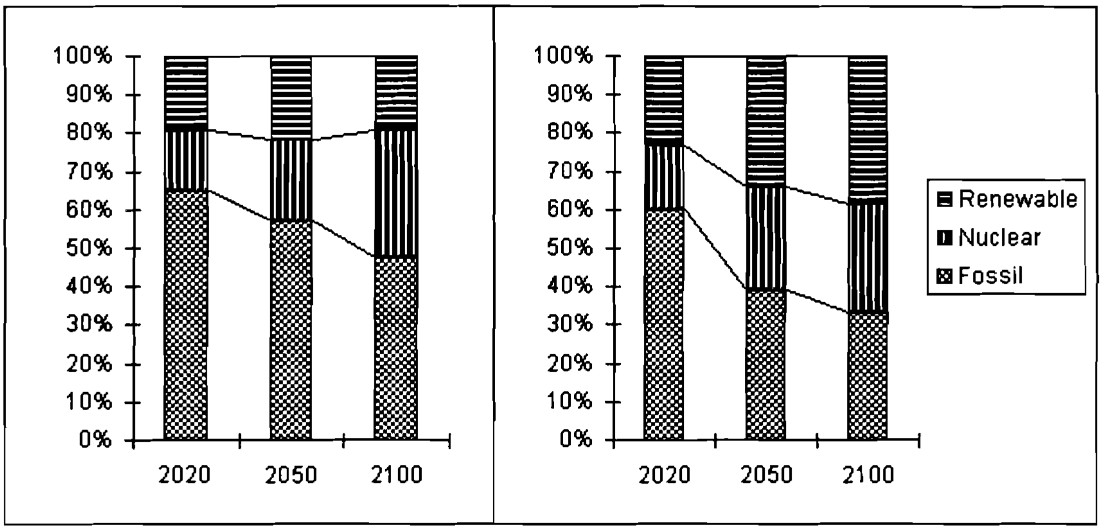


Figure 8. Global electricity production without (left) and with (right) changing investment costs [shares]

6. Final remarks

The method described in this paper allows to generate cost ranges for ten types of power plants based on a fairly large set of 603 independent estimates. By this it was possible to estimate costs for these power plants for different world regions and time periods. Model applications using theses data have shown, that the results improve, compared to runs, were constant cost figures were used for all regions over the complete time horizon.

As this experiment proved to produce valuable results, similar investigations should be performed for other variables, like efficiencies of power plants and costs of other technologies in the energy chain. The most limiting factor is the availability of a large enough data set to allow a meaningful disaggregation of the data to more regions and time periods. As one can see from this study some 600 estimates were needed to provide estimates for two regions and two time steps.

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