LBNL- 52559

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Learning and Cost Reductions for Generating Technologies in the National Energy Modeling System (NEMS)

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January 2004

The work described in this paper was funded by the Office of Atmospheric Programs of the U.S. Environmental Protection Agency and by the Office of the Assistant Secretary of Energy for Energy Efficiency and Renewable Energy, Office of Planning, Budget Formulation, and Analysis and prepared for the U.S. Department of Energy under Contract No. DE-AC03-76SF00098. The opinions expressed in this article are those of the authors and do not necessarily reflect those of the U.S. Environmental Protection Agency or the Department of Energy.

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Energy Efficiency and Renewable Energy
U.S. Department of Energy

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Acknowledgments

The authors would like to express their appreciation to Kristina Hamachi LaCommare, Jonathan Koomey, Skip Laiter, Chris Namovicz, Tom Petersik, and Alan Sanstad for reviewing this document.

List of Learning Terms

Learning – generally used to mean Technological Learning.

Learning-by-Doing (LBD) – Technological Learning from experience gained from capacity growth.

Learning Rate (LR) – Cost reduction per doubling of installed capacity.

Learning Curve – The shape of the Learning Function.

Learning Factor (LF) – A factor used in the calculation of an electricity generating plants' overnight costs. This value starts at 1.0 and can be reduced every year. It is calculated in two ways and the better or lower value is the one that is used. Method 1 calculates LF as a function of capacity growth, and the second method uses a predefined Minimum Annual Learning.

Learning Function – Also known as Wright's Equation, the relationship between cumulative production and costs.

Minimum Annual Learning (MAL) – Predefined by NEMS, this value is annually subtracted from 1.0 to determine the LF upper bound. For example, if MAL was defined as 0.05 for an 'XYZ' plant, then in year 0, the LF for 'XYZ' would be 1.0, in year 1 the LF would be 0.95, in year 2 LF would be 0.90, and so on. The MAL defined LF is important when the second method of calculating LF, from capacity growth, does not lead to as low an LF.

Technological Learning – the production of goods more efficiently (cheaper or more quickly) due to learning through experience. This paper will distinguish two types of Technological Learning in NEMS, Technological Optimism Learning and Learning-by-Doing.

Technological Optimism – The tendency for unproven designs to have unforeseen costs for the first few units actually built, i.e. cost expectations are always too optimistic. Technological Optimism Factor acts like a pessimistic factor.

Technological Optimism Factor– The actual counterbalancing factor that accounts for the uncertainty due to Technological Optimism by adding a premium to overnight costs.

Technological Optimism Learning – The reduction of the Technological Optimism Factor as installed capacity grows.

Abstract

This report describes how Learning-by-Doing (LBD) is implemented endogenously in the National Energy Modeling System (NEMS) for generating plants. LBD is experiential learning that correlates to a generating technology's capacity growth. The annual amount of Learning-by-Doing affects the annual overnight cost reduction. Currently, there is no straightforward way to integrate and make sense of all the diffuse information related to the endogenous learning calculation in NEMS. This paper organizes the relevant information from the NEMS documentation, source code, input files, and output files, in order to make the model's logic more accessible. The end results are shown in three ways: in a simple spreadsheet containing all the parameters related to endogenous learning; by an algorithm that traces how the parameters lead to cost reductions; and by examples showing how AEO 2004 forecasts the reduction of overnight costs for generating technologies over time.

1. Introduction

The Merriam-Webster dictionary defines the word "learn" as: to gain skill in, by study or experience. This work was motivated in part by an interest in understanding how newer technologies become more cost competitive over time. Technological learning leads to the production of goods more inexpensively. Technological learning as implemented in energy forecasting models describes the combined effect of economies of scale and the process of gaining manufacturing skill from repetition. Cost reductions are especially important for newer technologies, which are frequently limited in their ability to reach the marketplace by high initial costs, and which benefit most rapidly from technological learning.

This paper explains how the National Energy Modeling System (NEMS) incorporates endogenous learning into its cost calculations for power plants. The parameters that affect the magnitude of the learning for each of 21 electric generating technologies are laid out. Learning in NEMS is expressed as a percent reduction of overnight capital costs.

NEMS uses exogenously determined improvements to represent technological learning for demand side end-uses, heat rates, and oil and gas supply. This exogenous learning will not be covered in this paper. However, it should be noted that demand-side and supply-side learning are interactive (Laitner & Sanstad, 2003). Therefore, exogenous learning implemented in NEMS inputs reduces endogenous learning.

NEMS is a partial equilibrium energy economy model that projects supply, demand, new capacity, price of energy, emissions, and other parameters. Its forecast yields the Department of Energy's Annual Energy Outlook (AEO), which is frequently used for energy policy analyses (EIA, 2000).

A major part of this investigation involves figuring out how NEMS calculates cost reductions due to learning for each of 21 power plants types. Technological learning is represented two ways in NEMS, by *Learning-by-Doing* and by *Technological Optimism*. Technological Optimism is more limited and is only applied for the construction of the first 5 plants of any technology type. The total optimism cost reduction is 10% - 15% between the first and fifth units built. Learning-by-Doing, on the other hand, is applied to all incremental installed capacity as an overnight capital cost reduction of between 1% and 10% per cumulative installed capacity doubling.

Section 2 describes the origins of the Learning Function. Section 3 shows the relationship between learning and overnight costs for the electricity generating plant types represented in NEMS. Section 4 explains Technological Optimism. Section 5 details how Learning-by-Doing works and how the Learning Factor is calculated. Section 6 walks the reader through the Learning Factor calculation for a natural gas combined cycle plant as well as showing the calculation for an emerging technology, photovoltaics. Section 7 illustrates how Learning Factors and plant costs change throughout the AEO. Section 8 summarizes which parameters relate to technological learning. Section 9 identifies areas for further research.

2. What is Learning-by-Doing?

T. P. Wright, in 1936, was the first to characterize the relationship between increased productivity and cumulative production. He analyzed man-hours required to assemble successive airplane bodies. He suggested the relationship is a log linear function, since he observed a constant linear reduction in man-hours every time the total number of airplanes assembled was doubled. The reduction in man-hours is called learning-by-doing (LBD). The relationship between number assembled and time to assemble is called Wright's Equation or the learning function (Madsen *et al*. 2002). Wright's Equation, shown below, has been shown to be widely applicable in manufacturing.

$$\text{Learning Function: } C_N = C_0 * N^b \quad \text{where,} \qquad (1)$$

N is the cumulative production.
$\mathbf{C_N}$ is the cost to produce $\mathbf{N}^{th}$ unit of capcity.
$\mathbf{C_0}$ is estimated cost to produce the first unit.
b is the Learning Parameter, equal to ln (1-**LR**) / ln (2), where,
LR is the LBD Rate, or the cost reduction per doubling of capacity.

In the technology learning literature the term Progress Ratio is frequently used. It is the complementary value to LR, i.e. 1-LR.

The following hypothetical example, illustrates Wright's Equation. If the first two airplanes took 1000 and 800 hours to assemble respectively, then the LR for airplane assembly could be calculated as 20% and the Progress Ratio would be 80%. Wright's Equation projects future production time if the LR is known. Therefore, the fourth airplane should take 640 hours to assemble and the eighth, 512 hours. This learning curve is shown in Figures 1 and 2, below. These figures are based on the same data, but Figure 2 is plotted on a log scale to illustrate the log linear nature of the learning function.

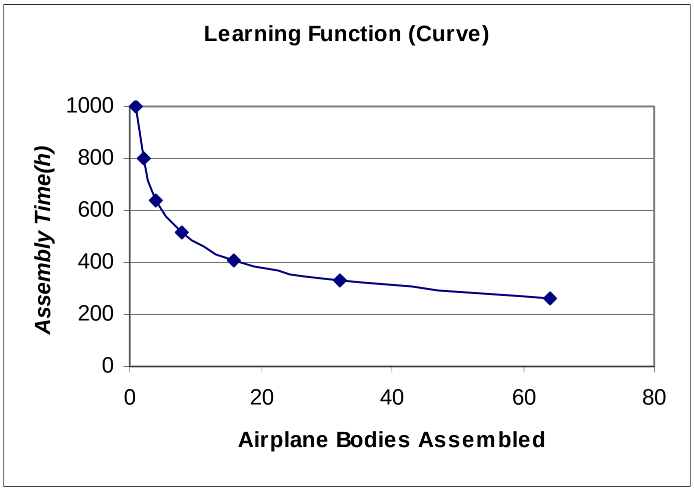


Figure 1. The Shape of the Learning Curve

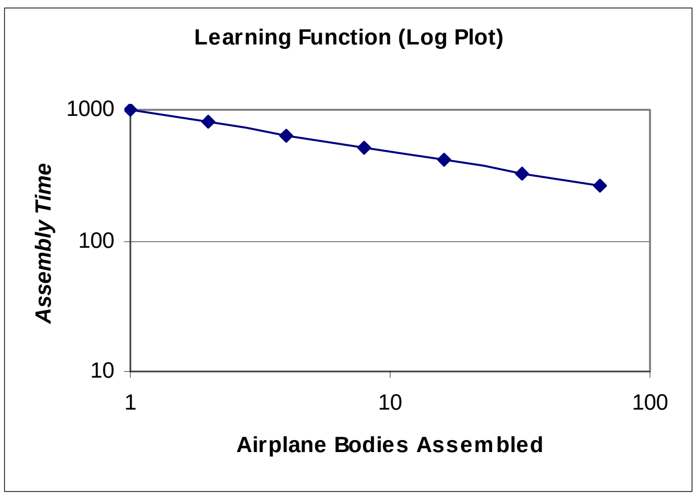


Figure 2. The Shape of Learning Curve on a Log Scale

The learning function described by Wright relates labor input reduction to experience. However, capital cost reductions have also been shown to correlate with experience (Mackay & Probert, 1998). Therefore, the learning function applied to electricity generating technologies in NEMS governs overall initial capital cost reductions not labor reductions.

2.1 Distinct Learning Stages

There is ample evidence from the literature that electricity generating technologies have distinct stages of development that correlate to different LRs. Colpier & Cornland (2002) identified three phases of development with different LRs for natural gas combined cycle plants. Grubler *et al*. (1999) described three stages similar to those used by NEMS. The latter authors identified three classifications to categorize different points in any technological development. *Mature Technologies* are those that have saturated the market, have well-known characteristics, and have limited potential for cost reductions due to learning. *Incremental Technologies* have niche market commercialization and have potential for significant cost reductions due to learning. *Radical Technologies* have almost no market share, and may never reach any significant commercialization, but their potential learning cost reductions are high.

The LRs that Grubler *et al*. (1999) associate with each classification are in Table 1, below. While conceptualizing technological development by three stages is pretty consistent in the literature, the LRs associated with each stage are not. Even the definition of maturity level for certain technologies is subject to interpretation. Unlike Grubler *et al*. (1999), NEMS considers Geothermal an incremental technology and Biomass a radical technology.

Table 1. Learning-by-Doing Rate by Classification

Technology Classification	Learning-by-Doing Rate	Examples: Electricity-Generating Technologies
Mature	0%	Combustion gas turbine, gas combined-cycle, conventional coal
Incremental	10-40%	Biomass, coal combined cycle, nuclear, and wind
Radical	High, potentially > 50%	Geothermal, solar-thermal, and solar PV

Source Grubler *et al*. 1999.

3. Capital Costs for Electric Generating Technologies in NEMS

In NEMS, technology penetration decisions take place in the Electricity Market Module's Electricity Capacity Planning Submodule (ECP). The AEO 2003 version of NEMS characterizes 21 available electric generating technologies. Their total overnight costs for the year 2002 are shown in the first column of Table 2. The total overnight cost for each technology is the product of four components. The four components are: the Initial Engineering Cost, a Technological Optimism Factor, a Project Contingency Factor, and a Learning Factor.

The Technological Optimism and Project Contingency Factors are related to cost uncertainty and can have values above 1.0. Cost reductions over time are driven by the reduction of either of the two components related to technological learning, the Technological Optimism and the Learning Factors. Sections 4 and 5 explain how these factors change. These two factors and the total overnight costs are recalculated and updated for every subsequent year. The first three components in Table 2 are predefined input values for the ECP. However, the optimism factor can be reduced over time.

Table 2. Total Overnight Costs and Cost Components for 2002, in NEMS

	Total Costs (01$/kW)	Initial Engineering Cost Estimates (01$/kW) derived	Technological Optimism Factor in 2002	Project Contingency Factor	Learning Factor in 2002
Scrbd Pulverized Coal	1155	1079	1	1.07	1.0
Integrated Gas CC	1367	1278	1	1.07	1.0
Gas/Oil Steam Turbine	1051	982	1	1.07	1.0
Existing CT	347	330	1	1.05	1.0
Conv CT	409	389	1	1.05	1.0
Adv CT	461	439	1	1.05	1.0
Existing Gas/Oil CC	467	444	1	1.05	1.0
Conv Gas/Oil CC	536	511	1	1.05	1.0
Adv Gas/Oil CC	608	563	1	1.08	1.0
Fuel Cells	2138	1851	1.10	1.05	1.0
Conventional Nuclear	7723	3527	1	2.19	1.0
Biomass (Wood)	1764	1570	1.05	1.07	1.0
Geothermal[a]	1531	1604	1	1.05	1.0
Mun Solid Waste	1461	1365	1	1.07	1.0
Hydroelectric	1046	951	1	1.10	1.0
Pumped Storage	2300	2091	1	1.10	1.0
Wind	1004	938	1	1.07	1.0
Solar Thermal[a]	2622	2450	1.10	1.07	1.0
Photovoltaic[a]	3956	3768	1.10	1.05	1.0
Dist. Gen. Base	804	766	1	1.05	1.0
Dist. Gen. Peak	966	920	1	1.05	1.0

[a] Geothermal, Solar Thermal, and Photovoltaic also receive a 10% capital cost credit.

3.1 Engineering Cost Estimates

The initial engineering cost estimates for overnight costs come from realized costs for more mature technologies. Mature technologies, such as existing combined cycle plants, have known costs. For the youngest technologies, which have no realized costs, EIA uses its analysts' best judgment coupled with engineering cost estimates taken from industry and government experts (EIA, 2002; Personal Communication with James Hewlett, EIA, Nov. 2002).

3.2 Technological Optimism Factor

The *Technological Optimism Factor* (TOF) is a contingency factor applied to the most immature generating technologies. Technologic Optimism is not the typical LBD discussed in the literature, but it is still learning through experience. EIA has identified a tendency for unproven designs to have unforeseen cost overruns for the first few units (EIA, 2002). In order to account for this tendency, the first five units have a TOF applied to the initial engineering estimates. This factor represents rapid learning over the course of the first few units built. The magnitude of this factor is determined by historical data and by econometric estimates originally performed by Ed Merrow at RAND (Personal Communication with James Hewlett, EIA, Nov. 2002). Section 4 explains the Technological Optimism in more detail.

3.3 Project Contingency Factor

The *Project Contingency Factor* (PCF) is a traditional risk factor applied to all technologies, mature or not. The PCF does not change from year to year. Except for nuclear plants, the PCF ranges from a high of 1.10 to a low of 1.05; conventional nuclear plants have a PCF of 2.19. PCF does not relate to learning.

3.4 Learning Factor

The *Learning Factor* (LF) is calculated based on each technology's capacity increase. The LF was explained along with Wright's equation in the previous section. The LF applies to all production and can change every year for every technology. The LF starts at 1.0 in 2002 for all technologies. A detailed explanation of how LFs are calculated follows in Section 5.

4. Technological Optimism Learning

Technological Optimism Learning (TOL), or the reduction of the TOF, is the learning associated with initial commercialization of electric generating plants. It only applies to technologies that are just beginning commercialization. While optimism sounds positive, the TOF is used to raise costs to offset unrealistic optimism.

Technological Optimism (TO) represents the difference between initial new technology cost estimates and actual first-of–a-kind costs by adding a premium to the first five units built of unproven technologies. TOL is the reduction of this premium to 1.0, and after the fifth unit is built, there is no longer any premium associated with TO. Cost reductions associated with TOL are significant but less powerful than the concurrent LBD reductions.

There are only four technologies that are young enough to have TO associated with them: fuel cells, biomass, solar thermal, and photovoltaic plants. The initial TOFs are shown in Table 3. In NEMS, the first plant is considered preexisting for uncommercialized technologies, so the premium applies to the first four plants built, which are plants numbers two through five. The TOFs decrease linearly to 1.0 as units two through five are built.

Table 3. Technological Optimism Factor Applied to Capital Costs when Less than Five of any Revolutionary Type Plants Exist

	Plant Size (MW)	Technological Optimism Factor, 1st plant	2nd plant	3rd plant	4th plant	5th plant
Fuel Cells	10	1.10	1.075	1.05	1.025	1.0
Biomass (Wood)	100	1.05	1.0375	1.025	1.0125	1.0
Solar Thermal	100	1.10	1.075	1.05	1.025	1.0
Photovoltaic	5	1.10	1.075	1.05	1.025	1.0

Source: Data from NEMS AEO 2003 input file *ecpdat* and source code file *ucape*

5. Learning-By-Doing (LBD) and Learning Factor Calculation

LBD in NEMS is the process first described by Wright that accounts for cost reductions due to manufacturing experience. LBD illustrates the relationship between cumulative production (experience) and the cost of the next unit of production. In NEMS, cost reductions are related to cumulative installed capacity, which is a surrogate for experience, and cost reductions are described by percent reduction in capital cost for each doubling of cumulative capacity. Cost reduction per doubling of capacity is based on maturity of the technology or vintage.

Equation (1) solves a technology's current production costs when three parameters are known: overnight costs for the first unit, $\mathbf{C_0}$, cumulative production, **N**, and progress ratio or LBD rate, **LR**. NEMS however, cannot use Equation (1) because the cost data available is for current capacity not for first unit of capacity, $\mathbf{C_0}$. Therefore, the learning function in NEMS takes on a slightly different form than the classic version, making use of current production cost data to calculate current production costs $\mathbf{C_N}$. AEO 2003 has collected data for capacity available in year 2002, **X**, and next unit costs in year 2002, $\mathbf{C_X}$, for each technology. Therefore, NEMS determines $\mathbf{C_N}$, by solving a variation of Equation (1).

$$C_N = C_X * LF_N \qquad \text{where,} \qquad (2)$$

X is the baseline capacity given in the initial year (2002 for AEO 2003).
$\mathbf{C_X}$ is the cost to produce the next unit, when cumulative capacity is **X**.
$\mathbf{LF_N}$ is the Learning-by-Doing Factor for capacity **N**, i.e. the percent reduction of the engineering cost estimates and **LF** is a function of **N**.

If NEMS can calculate the **LF** when production equals **N**, then Equation (2) can be used to solve for $\mathbf{C_N}$. $\mathbf{LF_N}$ can be found by substituting Equation (1), into Equation (2) giving:

$$C_0 * N^b = C_0 * X^b * LF_N \qquad (3)$$

Then reducing, rearranging, and solving for $\mathbf{LF_N}$ gives,

$$LF_N = N^b \;/\; X^b \qquad \text{or,} \qquad (4)$$

$$LF_N = a * N^b \qquad \text{where,} \qquad (5)$$

a is the parameter equal to $1/\,\mathbf{X^b}$, as used in NEMS for simplicity.

X and **b** are known constants in NEMS, while **N** is calculated annually. All the **X** and **b** values are explained and shown below in the following two sections.

5.1 Baseline Capacity, 'X'

The determination of Baseline Capacity is confusing as is shown in Table 4. NEMS defines **X** as either the Typical Unit Size or the actual cumulative capacity in 2002. *Typical Unit Size* is the average unit size, defined by NEMS for the purpose of calculating **X** and should not be confused with the increment by which new plants are added in NEMS. The rule is that if the typical unit size is greater than the 2001 cumulative capacity then **X** equals typical unit size. Otherwise, **X** is assigned the actual 2002 cumulative capacity.

Table 4. Vintage & Baseline Capacity, X (all units MW)

A	B	C	D	E	F
PLANT TYPE	Vintage	Typical Unit Size	Cumulative Capacity in 2001	Cumulative Capacity in 2002	'**X**', Baseline Capacity
Scrbd Pulverized Coal	Con.	600	498	498	600
Integrated Gas Comb Cycle	Evo.	550	1,958	2,022	2,022
Gas/Oil Steam Turbine	Con.	300	9,356	11,870	11,870
Existing Combustion Turbine	Con.	160	20,216	41,097	41,097
Conv Combustion Turbine	Con.	160	29,535	50,306	50,306
Adv Combustion Turbine	Evo.	230	299	299	299
Existing Gas/Oil Comb Cycle	Con.	250	20,908	20,908	20,908
Conv Gas/Oil Comb Cycle	Con.	250	39,389	60,045	60,045
Adv Gas/Oil Comb Cycle	Evo.	400	9,958	10,314	10,314
Fuel Cells	Rev.	10	-	-	10
Conventional Nuclear	Con.	1,350	498	4579	1,350
Biomass (Wood)	Rev.	100	9	9	100
Geothermal	Evo.	50	556	567	567
Mun Solid Waste	Con.	30	265	419	419
Hydroelectric	Con.	500	-	-	500
Pumped Storage	Con.	250	-	576	250
Wind	Con.	50	2,306	4,153	4,153
Solar Thermal	Rev.	100	-	1	100
Photovoltaic	Rev.	5	1	10	5
Distributed Generation-Base	Evo.	2	-	-	2
Distributed Generation-Peak	Evo.	1	-	-	1

Note: The definition of Baseline Capacity follows this logic. If Column C is greater than Column D, Column F equals Column C's value. Otherwise Column F equals Column E's value.

5.2 Learning Parameter, 'b' & Vintage

The Learning Parameter, **b**, assumes one of three values depending on what vintage the electric generating technology has been defined. These three vintages, revolutionary (Rev.), evolutionary (Evo.), or conventional (Con.), roughly correspond to three of the stages of technological development described in Grubler *et al*. (1999), Radical, Incremental, and Mature. Vintage by plant type is shown above in Table 4. **b** is defined by its relationship with the **LR**.

$$LR = 2^{b} \qquad \text{in other words,} \qquad (6)$$

$$b = \ln LR / \ln (2) \qquad (7)$$

b can be calculated when **LR** is known.
LR corresponds to vintage. Both values are shown in Table 5, below.

Table 5. NEMS Learning Parameters for Each Technology Classification

Vintage	**LR**	**b**, Learning Parameter
Revolutionary	10%	-0.152
Evolutionary	5%	-0.074
Conventional	1%	-0.0145

Note: There is one exception to this classification, MSW plants have 0% LR.

Even though a plant's initial vintage is predefined, there is one complication related to vintage. Over time, installed capacity increases and eventually a revolutionary plant can become evolutionary and an evolutionary plant can become a conventional one. Therefore, there must be some point defined when technologies are assumed to pass from one vintage to another.

5.3 Breakpoints

NEMS calls the inflections between vintages, *breakpoints* and these predefine when vintage advances. A revolutionary technology is redefined as an evolutionary technology after three doublings of capacity, i.e. when $\mathbf{N} = \mathbf{X} * 2^3$. An evolutionary technology is redefined as a conventional technology after five doublings of capacity, i.e. when $\mathbf{N} = \mathbf{X} * 2^5$. Potentially, even a revolutionary technology could become conventional after eight capacity doublings, i.e. when $\mathbf{N} = \mathbf{X} * 2^8$.

The AEO 2003 Reference Case forecasts that five plant types will have sufficient installed capacity gains to surpass their breakpoints before 2025. Photovoltaic and Fuel Cell technologies begin as revolutionary and become evolutionary. The two Distributed Generation plant types and the Advanced Combustion Turbine plant type begin as evolutionary and become conventional.

5.4 Cumulative Production and Learning Capacity, 'N'

NEMS differentiates between what it considers cumulative production, **N** for calculating capacity doublings, and total installed capacity. The value of **N** is not necessarily equal to the total installed capacity. Installed capacity growth is calculated annually in the ECP submodule. **N** is related to the installed capacity, but will henceforth be called *Learning Capacity*. There are potentially two adjustments made to actual total installed capacity, in order to calculate **N,** one adjusts higher and one lower. First, NEMS gives learning capacity credit to technologies with international experience. The capacity growth that should count towards international LBD is shown in Table 6. The second adjustment is based on maximum annual learning capacity growth.

5.4.1 International Learning

Manufacturing experience and economies of scale, which lead to learning, are not limited to domestic experience. There are two ways international capacity can impact domestic learning, through technology and people's LBD (Petersik 1997). First, companies that manufacture domestic power plant components may also produce similar components internationally. Second, international experience can lead to industry wide learning. To reflect this interaction, off-shore development is counted, but the amount of international capacity growth that NEMS accepts is limited in two ways. First, only a percent of the total international growth counts based on the extent to which the companies which manufacture, design, operate, and own the plants compete in the U.S. Second, no more than one standard size plant's worth of international capacity per year can count towards domestic learning (Personal communication with Thomas Petersik, EIA, Dec. 2001).

Table 6. International Capacity Growth Applied to Learning

Technology	Adv. Gas/Oil Comb Cycle
Percent Applied to Learning	75%
Year	
2002	475
2003	1425
Total Int'l Capacity	1900

Note: The Percent Applied row indicates what fraction of the International Capacity that counts towards the Learning from capacity growth. For example the 475 MW new capacity of Advanced Combined Cycle in 2002 only counts as 319 MW, (75% of 425) towards learning.

Source: NEMS input file, *eintlrn.*

Table 6 is rather abbreviated because all the other data from the input file is for earlier years. The international capacity file for NEMS was created many AEO versions ago and has not been updated. This component is out of date.

5.4.2 Limits to Learning Capacity, **'N',** Growth year-to-year

EIA feels, justifiably, that there should be an upper limit on LBD in any one year no matter how dramatic the one-year capacity growth may be; therefore, credited growth is limited to 50% beyond the previous year's installed capacity. In other words, when a technology experiences rapid growth, **N** has a maximum increase year-to-year of 50%, but any growth beyond 50% can count towards **N** in the following year.

5.5 Minimum Annual Learning

Equation (4) calculates the LF based on capacity growth for each technology, every year in order to recalculate the cost to build each plant. However, NEMS can reduce total overnight costs every year even if there is no capacity growth and no learning year-to-year because NEMS has built in Minimum Annual Learning (MAL). A minimum LF which constantly decreases each year is calculated differently than the LF from equation (4).

$$LF_2 = 1 - MAL_{vt,yr} \qquad \text{where,} \qquad (8)$$

LF_2 is an alternative LF based on MAL not Learning Capacity growth.
$MAL_{vt,yr}$ based on vintage and year, consult Table 7.

This is not to say that costs are reduced every year. The minimum LF for all years is predefined and correlates to vintage regardless of any or all installed capacity growth. If capacity growth leads to a lower LF than MAL, then the minimum LF is irrelevant. If, however, capacity growth leads to a higher LF than MAL does, the minimum LF is used. as a lower bound. MAL is shown in Table 7 below, and increases in a constant fashion.

Table 7. Minimum Annual Learning by Vintage by Year

	Rev	Evo	Con	Wind[1]
2003	0.87%	0.43%	0.22%	0.04%
2004	1.74%	0.87%	0.43%	0.09%
2005	2.61%	1.30%	0.65%	0.13%
2006	3.48%	1.74%	0.87%	0.17%
2007	4.35%	2.17%	1.09%	0.22%
2008	5.22%	2.61%	1.30%	0.26%
2009	6.09%	3.04%	1.52%	0.30%
2010	6.96%	3.48%	1.74%	0.35%
…	…	…	…	…
2015	11.30%	5.65%	2.83%	0.57%
…	…	…	…	…
2020	15.65%	7.83%	3.91%	0.78%
…	…	…	…	…
2025	20.00%	10.00%	5.00%	1.00%

[1]Wind Plants, though defined as Conventional, have only a 1% Minimum Learning by 2025. Wind plants are treated differently in NEMS because EIA determined that for wind plants learning leads to efficiency improvements rather than cost reductions (conversation with Chris Namovicz, EIA, March 2003).

5.6 Learning Curve by Vintage

TO and LBD both apply for production of the first 4 units built, i.e. units two through five. Therefore, the revolutionary technologies have cost reductions beyond 10% per doubling up to two and a quarter doublings. The shape of the learning curve in NEMS is shown in Figure 3, which has a log-log scale. This figure is an illustration of what the learning curve would look like for a technology that passes through all three stages. Therefore, the cost axis has no units associated with it as the starting point could be at any level. The shape of the curve is what's being pointed out and is consistent no matter the initial cost. The 'y' axis is where a revolutionary vintage technology begins. An Evolutionary Technology begins at the first vertical line, 2^3 or eight units built, and Conventional Technologies begin at the second vertical line, 2^8 or 256 units built.

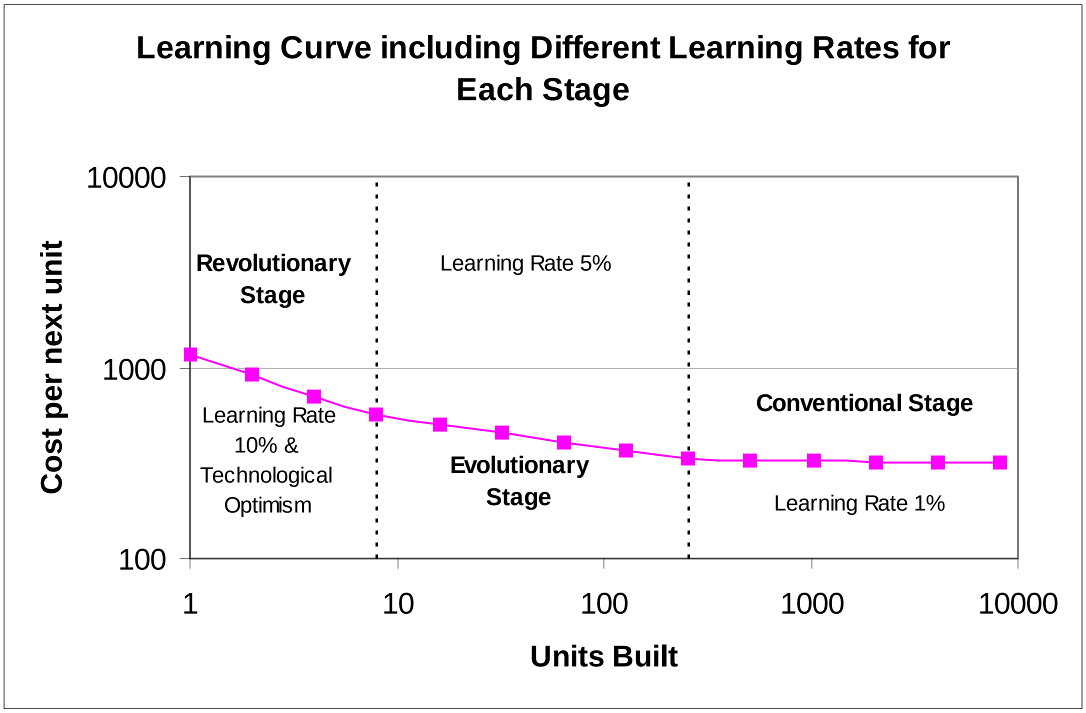


Figure 3. The Shape of NEMS's Learning Curve through each Vintage regardless of Plant Type, (Costs axis values are for scale only)

6. Learning Examples: Advanced Combined Cycle & Photovoltaic plants

In order to verify NEMS's learning calculation, the learning for each technology was calculated for every year and compared to the values calculated by NEMS. The learning factor and most of its related variables are not usually output by NEMS, but the ELOPTLC subroutine can output these variables, which made the verification much easier.

Using initial values for all the relevant variables, a spreadsheet model replicating the ELOPTLC code was written. Once the algorithm and the spreadsheet were set up, it took a little debugging to get the spreadsheet to match the NEMS output. This algorithm is included in the Appendix. A more simplified example of NEMS's learning calculation is shown below in Table 8, for an evolutionary plant, Advanced Gas/Oil Combined Cycle. The calculation of all the relevant variables each year, is included. Subsequently, a revolutionary turned evolutionary plant example, photovoltaic, is shown in Table 9.

This section will explain all steps needed to calculate the Learning Factor in NEMS. Then the reader is walked through the steps for an example Combined Cycle plant.

1. Identify the Baseline Capacity.
2. Identify the vintage of plant.
3. Calculate Learning Parameter, **b**.
4. Calculate $\mathbf{1/X^b}$ term, which is called **a** for simplicity.
    a. Identify the annual capacity growth from Electricity Capacity Planning Submodule.
5. Calculate Learning Capacity based on capacity growth.
6. Learning Factor calculated ($a* N^b$) based on values from #4 and #6 above.
7. Learning Factor calculated based on Minimum Annual Learning, Table 7.
8. Select Learning Factor.
9. Repeat steps 6 - 9 for years 2003 - 2025.

Working through the proceeding steps for an advanced natural gas combined cycle plant results in the following values.

1. 10314 MW from Table 5.
2. Given as Evolutionary.
3. Table 5 indicates that an Evolutionary plant has a **LR** of 5%, and that **b** equals negative 0.074.
4. From #1 and #3 above, **a** is calculated to be 1.981 / MW. NEMS calls this quantity parameter 'a' in order to be able to express the Learning Factor equation (4), more simply as $LF_N = a* N^b$
5. In 2003 the growth is 1069 MW, subtraction from the spreadsheet below, column $\mathbf{C_{year}}$. (11,383 MW – 10,314 MW).
6. Learning Capacity is equal to the actual capacity 11,383 MW, because 1069 MW is less than 50% of 10,314 MW.
7. $\mathbf{LF_{2003}}$ equals 0.993.

8. Minimal annual learning is 0.43%, Table 7, so the minimum learning factor is 0.996. (1.000 – 0.0043).
9. The lessor of #7 and #8 above, 0.993.
10. These values are shown in the following spreadsheet.
    -Step 6 is calculated in Column Learning Capacity.
    -Step 7 is Column LF.
    -Step 8 is Column minimum LF, and
    -Step 9 is Column Final LF

Table 8. Learning Factor Calculation for an Advanced Gas/Oil Combined Cycle Plant

Given:		Calculated:	
Vintage	Evolutionary	C_{base}	10314 MW
MAL per year	0.0043	b	-0.0740
Total Capacity	See Table	a	1.981 / MW
Typical Unit Size	400 MW	Learning Factors	See Table

	Total Capacity (MW)	Learning Capacity (MW)	LF (Calculated)	Minimum LF (from MAL)	Final LF
2002	10314	10314	1.000	1.000	**1.000**
2003	11383	11383	0.993	0.996	**0.993**
2004	11383	11383	0.993	0.991	**0.991**
2005	11383	11383	0.993	0.987	**0.987**
2006	14787	14787	0.974	0.983	**0.974**
2007	16965	16965	0.964	0.978	**0.964**
2008	24079	24079	0.939	0.974	**0.939**
2009	29206	29206	0.926	0.970	**0.926**
2010	41641	41641	0.902	0.965	**0.902**
2011	54850	54850	0.884	0.961	**0.884**
2012	69117	69117	0.869	0.957	**0.869**
2013	80512	80512	0.859	0.952	**0.859**
2014	91546	91546	0.851	0.948	**0.851**
2015	103612	103612	0.843	0.943	**0.843**
2016	108751	108751	0.840	0.939	**0.840**
2017	113699	113699	0.837	0.935	**0.837**
2018	120068	120068	0.834	0.930	**0.834**
2019	125661	125661	0.831	0.926	**0.831**
2020	133506	133506	0.827	0.922	**0.827**
2021	138159	138159	0.825	0.917	**0.825**
2022	148877	148877	0.821	0.913	**0.821**
2023	154798	154798	0.818	0.909	**0.818**
2024	167299	167299	0.814	0.904	**0.814**
2025	173197	173197	0.812	0.900	**0.812**

Table 9. Learning Factor Calculation for a Photovoltaic Plant

Given:		Calculated:	
Vintage	Revolutionary	C_{base}	10 MW
Vintage (post 2006)	Evolutionary	b	-0.152
MAL per year	0.0087	b (post 2006)	-0.074
MAL (post 2006)	0.0043	a	1.277 / MW
Total Capacity	See Table	a (post 2006)	0.958 / MW
Typical Unit Size	5 MW	Learning Factors	See Table

	Total Capacity (MW)	Learning Capacity (MW)	LF (Calculated)	Minimum LF (from MAL)	Final LF
2002	10	10	0.903	1.000	**0.903**
2003	14	14	0.857	0.991	**0.857**
2004	22	21	0.806	0.983	**0.806**
2005	29	28	0.768	0.974	**0.768**
2006	37	36	0.740	0.965	**0.740**
2007	47	46	0.721	0.961	**0.721**
2008	60	59	0.708	0.957	**0.708**
2009	70	69	0.700	0.952	**0.700**
2010	83	82	0.691	0.948	**0.691**
2011	95	94	0.684	0.943	**0.684**
2012	110	109	0.677	0.939	**0.677**
2013	125	124	0.670	0.935	**0.670**
2014	140	139	0.665	0.930	**0.665**
2015	158	157	0.659	0.926	**0.659**
2016	175	174	0.654	0.922	**0.654**
2017	193	192	0.649	0.917	**0.649**
2018	210	209	0.645	0.913	**0.645**
2019	228	227	0.641	0.909	**0.641**
2020	245	244	0.638	0.904	**0.638**
2021	263	262	0.634	0.900	**0.634**
2022	280	279	0.631	0.896	**0.631**
2023	298	297	0.629	0.891	**0.629**
2024	315	314	0.626	0.887	**0.626**
2025	333	332	0.623	0.883	**0.623**

Notes:

In 2007, PV is redefined as an Evolutionary vintage since it passes its breakthrough capacity point of 40 MW. Therefore, the MAL, 'b', and 'a' values are all redefined.

The Total Capacity is higher than the Learning Capacity starting in 2004 because of a minor code inconsistency.

7. Effects of Endogenous Learning in the Annual Energy Outlook Reference Case

The end result of all the learning calculations in NEMS is shown in Table 9. The plants that learn the most are photovoltaic, fuel cells, distributed generation-peak, biomass, and advanced combustion turbine plants. Three of these are revolutionary plants, wherein modest absolute installed capacity growth leads to a significant number of capacity doublings. Many of the 21 plant types only reach their minimum LF. The values in Table 10 that are the minimum LF values have been shaded. The minimum values can be verified by using Equation (8), with the values from Tables 7 & 4 for MAL, year, plant, and vintage.

Table 10. Learning Factors by Plant Type

Plant Type	2005	2010	2015	2020	2025
Scrbd Pulverized Coal	0.99	0.98	0.96	0.94	0.94
Integrated Gas Comb Cycle	0.99	0.97	0.94	0.92	0.90
Gas/Oil Steam Turbine	0.99	0.98	0.97	0.96	0.95
Existing Combustion Turbine	0.99	0.98	0.97	0.96	0.95
Conv Combustion Turbine	0.99	0.98	0.97	0.96	0.95
Adv Combustion Turbine	0.97	0.84	0.77	0.76	0.76
Existing Gas/Oil Comb Cycle	0.99	0.98	0.97	0.96	0.95
Conv Gas/Oil Comb Cycle	0.99	0.98	0.97	0.96	0.95
Adv Gas/Oil Comb Cycle	0.99	0.90	0.84	0.83	0.81
Fuel Cells	0.97	0.73	0.69	0.68	0.68
Conventional Nuclear	0.97	0.95	0.95	0.95	0.95
Biomass (Wood)	0.97	0.93	0.89	0.84	0.75
Geothermal	0.99	0.94	0.92	0.90	0.88
Mun Solid Waste	0.99	0.98	0.97	0.96	0.95
Hydroelectric	0.99	0.98	0.97	0.96	0.95
Pumped Storage	0.97	0.97	0.97	0.96	0.95
Wind	0.99	0.99	0.99	0.99	0.99
Solar Thermal	0.97	0.93	0.89	0.84	0.80
Photovoltaic	0.77	0.69	0.66	0.64	0.62
Distributed Generation-Base	0.99	0.86	0.77	0.77	0.77
Distributed Generation-Peak	0.97	0.84	0.76	0.74	0.72

The total effect over time of technological learning on costs is shown in Table 10. The costs shown in the year 2002 column are identical to those from Table 2. The last column shows the percent cost reduction over the forecast horizon. The percent reduction is identical to the LF for all but six plant types. The cost reductions for the two Distributed Generation plant types are related to both the LF and some learning exogenous to NEMS, which reduces the engineering cost estimates over time. No other technology has predefined cost estimate reductions. The cost reductions for the four revolutionary plants, Fuel Cells, Biomass, Solar Thermal, and Photovoltaic result both from the LF and from the reduced technological optimism factor.

Table 11. Overnight Capital Costs by Plant Type ('01$/kW)

Plant Type	2002	2010	2015	2020	2025	2002 - 2025 % cost reduction
Scrbd Pulverized Coal	1155	1128	1103	1087	1081	6%
Integrated Gas Comb Cycle	1367	1320	1290	1260	1231	10%
Gas/Oil Steam Turbine	1051	1032	1021	1009	998	5%
Existing Combustion Turbine	347	341	337	333	329	5%
Conv Combustion Turbine	409	402	397	393	388	5%
Adv Combustion Turbine	461	389	355	351	348	24%
Existing Gas/Oil Comb Cycle	467	458	453	448	443	5%
Conv Gas/Oil Comb Cycle	536	527	521	515	509	5%
Adv Gas/Oil Comb Cycle	608	548	512	503	493	19%
Fuel Cells	2138	1428	1341	1329	1329	38%
Conventional Nuclear	7723	7316	7305	7299	7299	5%
Biomass (Wood)	1764	1602	1509	1435	1272	28%
Geothermal	1516	1428	1393	1361	1334	12%
Mun Solid Waste	1461	1436	1420	1404	1388	5%
Hydroelectric	1046	1028	1016	1005	994	5%
Pumped Storage	2300	2232	2232	2210	2185	5%
Wind	1004	994	992	990	989	1%
Solar Thermal	2596	2360	2260	2149	2039	21%
Photovoltaic	3917	2462	2346	2270	2220	43%
Distributed Generation-Base[a]	804	692	617	617	617	23%
Distributed Generation-Peak[a]	966	807	737	715	694	28%

[a] Note DG capital costs are reduced over time exogenously.

8. Summary

This paper has tried to lay bare how NEMS comes up with new Electricity Generating plant costs. Engineering Cost Estimates are the starting point for plant costs. Technological Learning is used to forecast cost reductions for all technologies other than distributed generation. The cost reductions usually relate to installed capacity growth though there is built in minimum cost reductions regardless of growth. In AEO 2003 reference case, 2 technologies have no installed capacity growth.

There are six parameters that affect Technological Learning in NEMS.

1. Baseline Capacity, which is the starting point for counting doublings of capacity.
2. Learning Capacity growth year-to-year. Which determines the number of doublings annually.
3. Learning Rate, which affects magnitude of cost reduction per doubling of capacity.
4. Minimum Annual Learning, which reflects a minimum cost reduction regardless of capacity growth.
5. Vintage, there are three classes, each class has its own Learning Rate and Minimum Annual Learning.
6. Technological Optimism Factor, which is a premium added to Engineering Cost Estimates just for the plant types of the youngest Vintage. This raises initial costs for year 2002 beyond Engineering Cost Estimates. Beyond 2002, this factor helps explain cost reductions, as this premium is phased out.

9. Further Research Needs

As with most studies, new questions have arisen during this analysis. There are also areas where the analysis could be improved. Three of the key areas requiring additional research are highlighted below.

1. Do cost reductions from Technological Learning have a significant effect on new installed capacity in NEMS? Policy studies using NEMS frequently are interested in potential fuel switching. Of course cost is only one parameter evaluated by NEMS to determine which technologies are chosen for new installed capacity. LBL-NEMS could evaluate scenarios with more and less technological learning to better determine how concurrent cost reductions affect the forecast for new installed capacity.

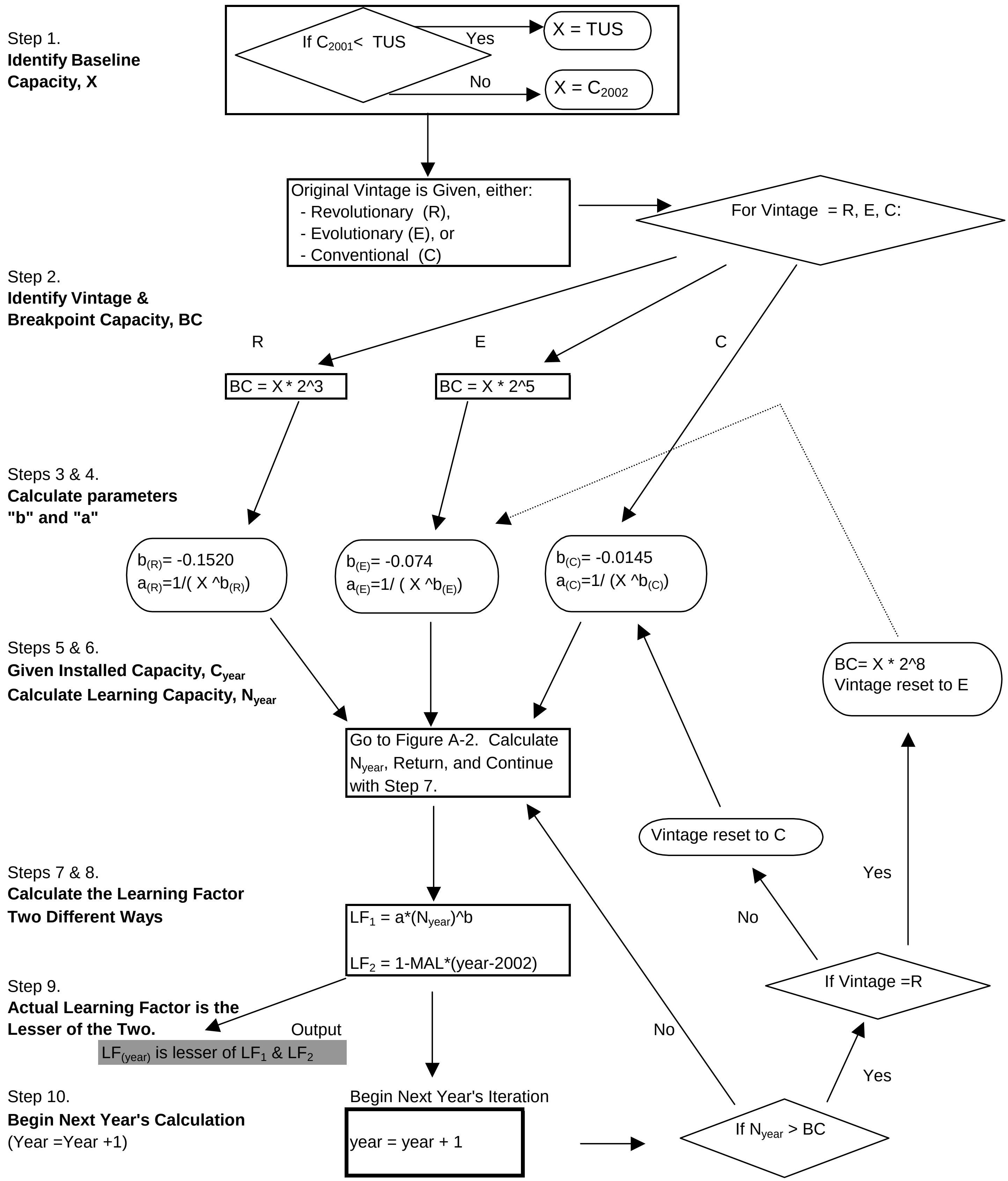
2. Why are the learning rate definitions in NEMS, particularly for Revolutionary and Evolutionary plants, so different than those found in other studies? Many studies (Colpier & Cornland, 2002; Grubler *et al*. 1999; Neij, 1997; Mackay and Probert, 1998), suggest learning rates between 10% and 30% per capacity doubling for mass-produced technologies. The literature seems to show a wide potential range for learning rates for the youngest technologies. A deeper analysis is required to understand why this discrepancy exists. For example, NEMS uses a beginning learning rate of 10% for PV, adding in the reduction from Technologic Optimism, the effective rate starts at 12.5% and by 2007 the learning rate reaches 5%. However, Grumbler et al., Mackay & Probert, and Neij all identify 20% as historical learning rates for PV. This significance of this and other discrepancies should be examined further.

3. NEMS is updated annually, so the data in this paper should be updated every few years. Technological Learning for wind plants, for example, is treated differently in AEO 2003 than it was in previous versions of AEO.

10. Appendix – Learning Algorithm

This appendix illustrates NEMS's learning factor algorithm and follows the logic used in the *ucape* source code. The first page shows a schematic representation of the algorithm. The ten steps are briefly explained on second page. The third page defines the notations or abbreviations used. The last page shows Step 6 of the algorithm, which is complicated enough to warrant it own schematic.

Figure A-1 NEMS's Learning Factor Algorithm



Notes regarding for Learning Factor Algorithm

Step 1. Identifies the Baseline Capacity, which is needed to calculate parameter 'a' and Breakpoint Capacity.

Step 2. Identifies the vintage, which determines the value for parameter 'b' and helps determine the Breakpoint Capacity. Breakpoint Capacity is the actual capacity at which a plant's vintage changes. Only four plants in AEO 2003 surpass their Breakpoint Capacities and change vintage; Fuel cells, Photovoltaic, and Biomass plants change from Revolutionary to Evolutionary vintage, while the Advanced Combustion Turbine plants change from Evolutionary to Conventional vintage.

Steps 3 & 4. Calculates parameters "a" and "b" which help calculate the Learning Factor in Step 7.

Step 5. Identifies installed capacity for a given year, C_{year}.

Step 6. Is the calculation of the Learning Capacity, shown in Figure A-2. Learning Capacity is calculated from the actual capacity, the previous year's capacity, previous year's Learning Capacity, and the typical unit size. This step applies rules about the minimum value for Learning Capacity and the maximum year-to-year Learning Capacity increase. There are five possible ways to calculate Learning Capacity depending on the situation.

Step 7. Calculate Learning Factor the first way, from Learning Capacity.

Step 8. Calculate Learning Factor the second way, from the minimum annual learning.

Step 9. Choose actual Learning Factor, the lesser of Step 7 and Step 8.

Step 10. Next year starts and the algorithm repeats itself starting at Step 5, unless the plant type has surpassed the Breakpoint Capacity. If so, the vintage is redefined and the current year begins at Step 3.

Diamonds are decision boxes.
Ovals are variable definition steps.

Variables – known

C_{2001} 2001 Capacity
C_{2002} 2002 Capacity
C_{year} Capacity for "year"
MAL Minimum Annual Learning
TUS Typical Unit Size

Variables – calculated

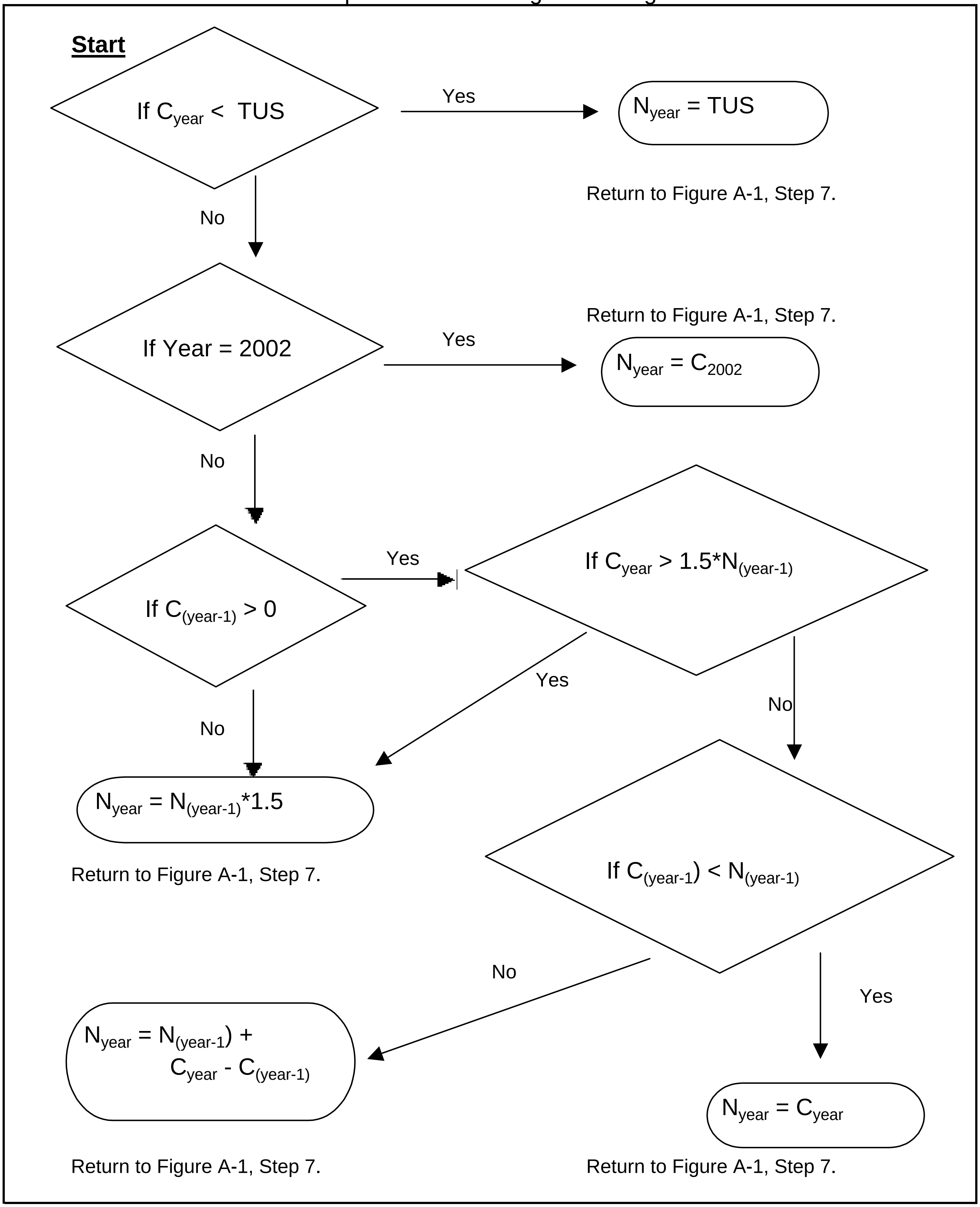
N_{year} Learning Capacity for "year"
LF_1 Learning Factor calculated from Learning Capacity
LF_2 Learning Factor calculated from the MAL
LF_{year} Learning Factor for "year", the lower of LF_1 and LF_2
BC Breakpoint Capacity is the capacity which defines when a Revolutionary or Evolutionary plants' vintage is reclassified.

'a' parameter in Learning Function
'b' parameter in Learning Function

X Baseline Capacity used to calculate vintage, Breakpoint Capacity and 'a'.

The only time values for vintage, BC, 'b', and 'a' are redefined is when an Evolutionary or Revolutionary plants' vintage is reclassified.

Figure A-2 Flowchart to Calculate Learning Capacity.
Step 6 of the Learning Factor Algorithm



Note: This last decision box reflects a minor code inconsistency, which does not affect the results materially. The 'No' and 'Yes' should be switched in the source code. Fuel Cells and Pumped Storage are most affected by this inconsistency. If corrected, the net affect would be an approximately 0.5% reduction in overnight costs.

11. References

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