Supporting Information: The energy balance of the global photovoltaic (PV) industry - is the PV industry a net energy provider?

Michael Dale*,† and Sally M. Benson‡

Global Climate and Energy Project, Stanford University, USA, and Energy Resources Engineering, Stanford University, USA

E-mail: mikdale@stanford.edu

Global installed capacity of different PV technologies

Data on global PV installed capacity [GW] between 2000 and 2010 shown in Table SS1 has been taken from (*1–3*). This data has been combined with data on market share [%] of PV technologies: single-crystal silicon (sc-Si), multi-crystaline silicon (mc-Si), ribbon silicon, amorphous-silicon (a-Si), cadmium telluride (CdTe), copper indium gallium (di)selenide (CIGS) and other (mainly polymer) from (*4*) to determine the installed capacity [GW] for each technology. We assume that market share defined installed capacity for each techology in 2000 and thereafter (2001-2010) the market share is allocated across *capacity additions* [GW/yr] for that year. Data for 1999 and 2011 has been estimated by extrapolating annual growth rates. Polymer PV was not included in our analysis due to lack of data.

*To whom correspondence should be addressed
†Global Climate and Energy Project, Stanford University, USA
‡Energy Resources Engineering, Stanford University, USA

Table S1: Installed capacity of the different PV technologies in GW, using data from (*1–4*)

Year	**Installed capacity [GW]**						
	sc-Si	mc-Si	Ribbon	a-Si	CdTe	CIGS	Other
1999E	0.40	0.52	0.04	0.11	0.01	0.00	0.00
2000	0.49	0.64	0.05	0.13	0.01	0.00	0.00
2001	0.57	0.75	0.06	0.15	0.01	0.00	0.00
2002	0.73	0.98	0.09	0.19	0.01	0.01	0.00
2003	0.96	1.30	0.12	0.23	0.01	0.01	0.00
2004	1.25	1.82	0.16	0.27	0.03	0.01	0.00
2005	1.65	2.43	0.19	0.32	0.04	0.02	0.00
2006	2.34	3.38	0.24	0.40	0.07	0.02	0.00
2007	3.33	4.44	0.30	0.51	0.13	0.03	0.00
2008	5.75	7.04	0.42	0.81	0.41	0.07	0.00
2009	8.97	11.06	0.55	1.24	0.94	0.14	0.00
2010	14.62	18.87	0.76	2.28	2.45	0.41	0.13
2011E	20.24	26.13	0.92	3.01	4.48	0.64	0.20
Growth rate [%] 1999-2011	38	37	18	32	86	60	51
Growth rate [%] 2005-2010	56	50	32	48	133	84	51

Energy payback time (EPBT) and industry growth

Grimmer (1981) defines the relationship between the fractional re-investment, f [%], the $EPBT$ [yrs] of plants comprising the industry and the growth rate, r [%/yr] for a growing energy production industry as $r = \frac{f}{EPBT}$ (*5*). Using this relationship, Figure SS1 shows the contours of f (sloping diagonal lines) on a log-log plot. A fractional re-investment of 100% marks the breakeven threshold. Green lines in the bottom left half of the digram represent the positive net energy regime, $f \leq 100\%$, red lines in the top right represent the negative net energy regime. To make use of the plot, we can choose any two of either the growth rate (left axis), the EPBT (bottom axis), or the fractional re-investment (diagonal contours). Assuming we have a device technology with an EPBT of 2 yrs and want to limit the fractional investment to 80%; what is the fastest rate at which an industry based on deployment of such devices could grow without energy subsidy? We trace up from the bottom axis at EPBT = 2 yrs until we meet the sloping fractional re-investment line, f = 80%. We then trace horizontally from this point to meet the vertical axis at a growth rate of 40

%/yr. Since we know that the current average growth rate of the PV industry is 40%, we can trace horizontally across at this value to discover that, for the PV industry as a whole to be a positive net energy provider (i.e. with a fractional re-investment of less than 100%), the EPBT must be below 2.5 yrs.

If an industry is a net energy sink, there are three means by which it may cross the breakeven threshold: (1) decrease the EPBT of system production, i.e. move across the plot horizontally from right to left; (2) decrease the rate of growth, i.e. move vertically down the plot or; (3) some combination of (1) and (2)

Derivation of breakeven threshold conditions

From Grimmer we have:

$$f = r\mathrm{EPBT} = r\frac{\mathrm{E}_{con} + \mathrm{E}_{op} + \mathrm{E}_{d}}{\dot{\mathrm{E}}_{g}} \tag{1}$$

Since $\mathrm{E}_{con} \gg \mathrm{E}_{op}$ and $\mathrm{E}_{con} \gg \mathrm{E}_{d}$ and we assume that t_{con} = 1 year, then we may say:

$$\frac{\mathrm{E}_{con} + \mathrm{E}_{op} + \mathrm{E}_{d}}{\dot{\mathrm{E}}_{g}} \simeq \frac{\dot{\mathrm{E}}_{con}}{\dot{\mathrm{E}}_{g}} \tag{2}$$

Hence, 1 may be re-written as:

$$\frac{f}{r} = \frac{\dot{\mathrm{E}}_{con}}{\dot{\mathrm{E}}_{g}} \tag{3}$$

From which we may discern the following conditions:

$$r > \frac{\dot{\mathrm{E}}_{g}}{\dot{\mathrm{E}}_{con}} \Rightarrow f < 1 \Rightarrow \text{energy sink} \tag{4}$$

$$r < \frac{\dot{\mathrm{E}}_{g}}{\dot{\mathrm{E}}_{con}} \Rightarrow f > 1 \Rightarrow \text{energy source} \tag{5}$$

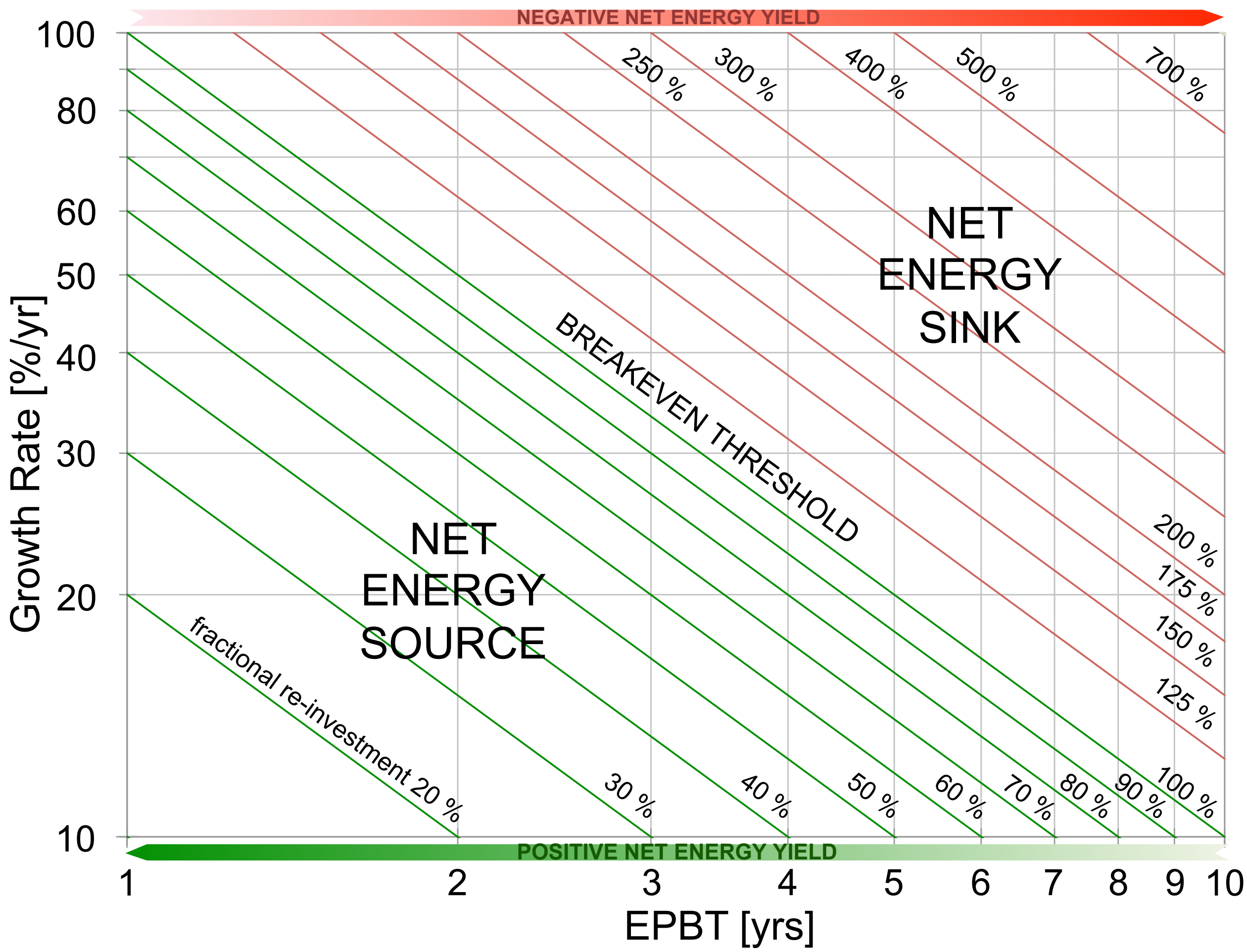

Figure S1: Growth rate [%/yr] as a function of energy payback time (EPBT) [yrs] for a number of fractional re-investment rates [%] (diagonal lines). Red lines indicate negative net energy yield and green lines indicate positive net energy yield.

Capacity factor of PV installations

The capacity factor of an energy generation system is a measure of the actual output from the system, normalized by the maximum theoretical output from the system if it operated at nameplate capacity all of the time. For a PV system, the capacity factor will be a function of many factors: the insolation at the location of the system - itself a function of latitude as well as weather conditions; the tilt of the installed PV panel; maintenance of the system and shadowing due to nearby obstacles.

The data for the capacity factor of world-wide PV installations was derived from national level data on installed capacity and annual generation from the EIA (*2*) and the UN (*3*). There are a number of issues with the data including:

- a disparity in the installed capacity for the US between the two datasets by a factor of nearly four – the EIA has installed capacity in 2008 of 536 MW, the UN has 1960 MW;
- a drop in the UN estimate for installed capacity in Denmark between 1996 and 1998 from 39 MW to 1 MW with no data for 1997;
- the calculated capacity factor for the US from the UN data in 1990 is 1056%;
- the calculated capacity factor for Sweden from the UN ranging between 30-45%, during the years 1990-1995;
- the calculated capacity factor for India from the EIA ranging between 70-108%.

Many of these issues were resolved by only using data from 2005-2008 for the analysis. Disparity between the two datasets was not resolved.

Another issue worth mentioning is potential disparity between capacity installations and power generation. The measurement of installed capacity is a measure of a stock at one moment in time, say December 31st. The measure of generation is the total flow over a period of time, say one year measured between January 1st and December 31st. Any capacity installed mid-way through the year will not have had a full year in which to generate electricity, hence the capacity factor will be decreased. This effect will be exacerbated when the industry is growing more rapidly.

An industry growing from installed capacity K_0 [GW] at time t_0 [yrs] exponentially at rate r [1/yr] is plotted in Figure 4. The year end measure of installed capacity taken at time t_1 gives K_1. Generation by the industry between t_0 and t_1 (assumed to be 1 year) is G [TWh]. We may define two separate capacity factors for the industry:

1. κ_m is the measured capacity factor based on the year-end installed capacity, K_1;
2. κ_a is the 'actual' device capacity factor based on the capacity $K(t)$ growing exponentially throughout the year.

The generation from the system can be defined:

$$G = \gamma\kappa_a \int_{t_0}^{t_1} K_0 \mathrm{e}^{rt} dt = \gamma\kappa_m K_1 \tag{6}$$

where γ is the conversion factor $\left(\frac{8760}{1000}\right)$ from GW to TWh. Re-arranging to find the ratio $\frac{\kappa_m}{\kappa_a}$ gives:

$$\begin{aligned} \frac{\kappa_m}{\kappa_a} &= \frac{\gamma \int_{t0}^{t1} K_0 \mathrm{e}^{rt} dt}{\gamma K_1} \\ &= \frac{\left[K_0 \mathrm{e}^{rt_1} - K_0 \mathrm{e}^{rt_0}\right]}{rK_1} \\ &= \frac{1}{r}\left(\frac{K_1 - K_0}{K_1}\right) \\ &= \frac{1 - \mathrm{e}^{-r}}{r} \end{aligned} \tag{7}$$

(8)

At a growth rate of 40% per year, the ratio $\frac{\kappa_m}{\kappa_a} = 0.85$, such that a measured capacity factor of $\kappa_m = 10\%$ is representative of an actual device capacity factor of $\kappa_a = 11.8\%$. Capacity factors were adjusted using this method to develop the distribution function used in Monte Carlo simulation.

Financial and energy costs of PV systems

In Figure SS2, we plot breakdowns of both the financial (*6*) and energy costs (*7*) incurred at various stages in the crystalline silicon PV system production process. The majority of financial costs (59%) occur in the last two stages involving the frame manufacture and module assembly as well as the balance of system and installation costs (*6*). The majority of energetic costs (57%) involve the extraction and purification of polysilicon and the production of PV wafers (*8*). Stoppato (2008) calculates that 90% of the inputs to multi-crystalline silicon module manufacture are in the form of electricity (*9*).

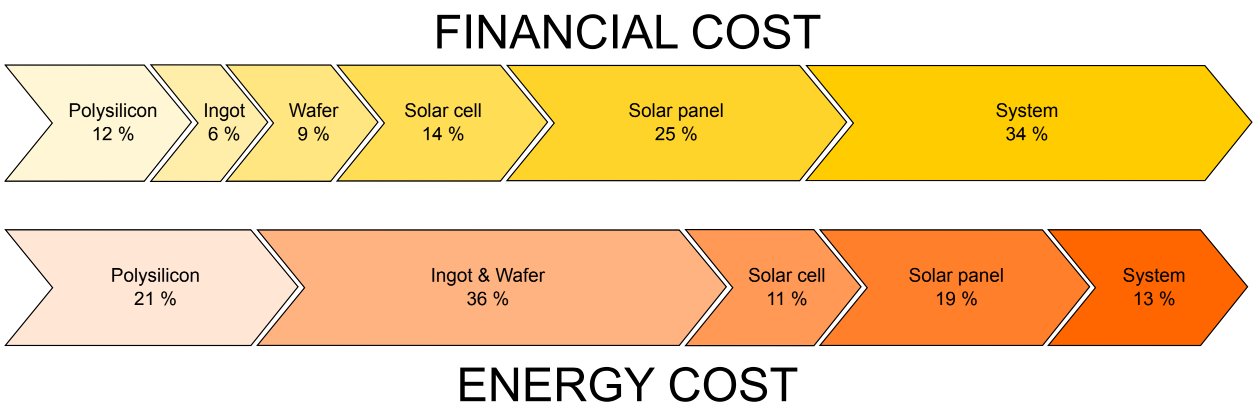

Figure S2: Breakdowns of the financial (top) and energetic (bottom) costs of crystalline silicon PV system production from material extraction through to system installation.

Estimates for the cumulative electrical energy demand (CE_eD) for each of the PV technologies are presented in the accompanying PV CED.xlsx file in the Supporting Information.

Energy discounting

Hannon (1982) is one of the few papers that has discussed the issue of energy discounting (*10*). Hannon uses a standard time based discounting procedure, stating

> To correct for differences in the time at which processing energies are committed for use a standard continuous-discounting function $e^{-\lambda t}$ was employed.

> The discount rate λ is the mechanism by which. 1 believe, society implicitly expresses its desire to convert a present surplus energy into an energy-transformation process so that a greater surplus of energy can be created in the future, rather than consuming the energy now for purposes such as home heating, leisure living, and certain types of food consumption. Whereas it is usually believed that people discount the total dollar value of goods and services, it is not inconceivable that they also discount energy. The apparent dollar discount rate might be viewed as a composite of the discount rates of the various physical inputs to produce each good or service.

The issue of discounting energy is fraught with methodological difficulties. One obvious question arises: should the discount rate λ be positive or negative? Standard economic analyses assume that some positive return on investment could be made by investing rather than consuming in the present. As such, the discount rate is often assumed to be positive. A positive discount rate essentially entails that a unit of value is worth *less in the future* than in the present. Could the same argument be made for energy? Investments of energy in the present can certainly be made to yield positive returns in the future, evidenced by energy-return-on-investment figures of greater than unity. However, energy discounting is very rarely done in either net energy analyses, nor in long-term energy projections as made by the International Energy Agency, Intergovernmental Panel on Climate Change or the US Energy Information Administration. The implicit justification (because it is never discussed explicitly) presumably being that according to the First Law of Thermodynamics, a unit of energy is equal today, tomorrow and for all time.

Might an argument be made for a *negative* discount rate for energy? This would entail that a unit of energy be *more valuable* in the future than in the present. Certainly, the efficiency with which energy is converted into secondary carriers and products and services is steadily increasing over time. Additionally, the energy intensity of society is increasing the financial yield per unit of energy ‘consumed’. These increases would suggest that energy does become more valuable over time, supporting the use of a negative discount rate.

In the present analysis, we have chosen to use a discount rate of zero for energy flows. The reason for this is two-fold. Firstly, because this is the standard practice in (net) energy analysis. Secondly, because the main comparison of inputs and outputs is of energy flows within the same time period.

Meta-analysis

A recent meta-analysis and harmonization project has been carried out by researchers at NREL and a number of other institutions to determine the distribution in GHG emissions from a variety of electricity production technologies over their entire life-cycle. Methodological details are provided in Heath and Mann (*11*). The results have been published in a special issue of the Journal of Industrial Ecology. We have carried out a meta-analysis of estimates of the cumulative energy demand (CED) of PV system manufacture and installation. The process involved a number of stages including: initial literature search, literature screening, data collection, commensuration of system boundaries and units.

Literature search

Searches were made of a number of publication types including peer-reviewed journals, industry reports, reports by national agencies, for example the US Department of Energy (DOE) and unpublished work including conference papers and doctoral theses. The search terms included the word “PV” with the following phrases:

- “embodied energy”,
- “cumulative energy demand”,
- “life cycle inventory”,
- “life cycle assessment”,

- "energy payback time",
- "net energy ratio" (NER),
- "energy yield ratio" (EYR),
- "energy return on investment",
- "EROI"

The initial search returned close to 500 results.

Literature screening

A number of criteria were used to screen the initial results:

- Study should be in English.
- The study should be original research or should reference data used.
- Study should give numeric data on net energy metric, e.g. CED, NER.
- The studies should include explicit data on energy inputs to the PV system manufacturing process, for example, a study stating only the energy payback time for a PV system with no other supporting data would not pass the screening.

Commensuration of study boundaries and data

The desired result for the meta-analysis was the CED of an installed PV system in units of kWh of electricity consumed per W of PV system capacity [kWh_e/W_p]. A number of methods were used to allow comparison of results:

- Data given in terms of primary energy was changed to electricity equivalents using conversion factors given in the study. If no conversion factor was given, a standard conversion factor of 30% was used.

- Where data was given in terms of energy inputs per unit of PV system area, e.g. MJ/m^2, this was converted to per unit capacity inputs by using rated PV system efficiency and standard test conditions (STC) irradiance of 1000 W/m^2. If no efficiency was given, the study was not used.

- If data was given in terms of an energy intensity, i.e. energy inputs per unit of electricity produced, e.g. [MJ/kWh_e], this was converted to per unit capacity inputs by either:

  - using the capacity factor, i.e. the ratio of the average power output to nameplate capacity of the PV system or,
  - using the total lifetime electricity production of the PV system or,
  - using the annual electricity production of the PV system and the lifetime of the PV system, if no lifetime was given, the system was assumed to have a nominal lifetime of 25 years,
  - if neither capacity factor or electricity production were given, the study was not used.

The data from the studies was categorized according to appropriate stage in the PV system production process: materials extraction and processing, PV cell manufacture, PV module assembly (including frame and glass manufacture), and PV system installation including site preparation and manufacture of balance of system (BOS) components, such as inverters, grid interconnections and tracking systems. Only studies that gave data for the energy inputs to the full PV system were included in the final meta-analysis.

Alternative models of decreasing CE_eD

There is some discussion in the literature to the usefulness of learning curves (*12*), hence, a number of alternative learning models were applied to test which gave the best fit with the data. The results are shown in Table S2.

In 4 cases, the best fit (shown in bold) was provided by a power law function using cumulative production, K [MW], as the independent variable. In one case (CdTe system) the best fit was provided by an exponential function again using cumulative production as the independent variable. In 3 cases, the best fit was provided by a linear function with time, t, as the independent variable.

Unfortunately, these models are unsuitable, as they predict CED = 0 (a clear violation of the First and Second Laws of Thermodynamics) in the years 2011, 2013 and 2017, respectively. In two cases, the second-best fit is provided by a power law function using cumulative production as the independent variable. In the last case (mc-Si system), the second-best fit is provided by a power law function with time as the independent variable.

As such, a power law function with cumulative production as the independent variable provides the best (physically viable) fit to the data in six out of the eight cases. This provides good support for the model used in projecting CE_eD.

Table S2: Alternative learning models applied to the meta-analysis CE_eD data using both time [yrs] and cumulative production [MW] as the independent variable.

			Linear		Exponenial		Power	
Technology	Boundary	Independent variable	Function	R^2	Function	R^2	Function	R^2
a-Si	Module	Time, t, [yrs]	$290 - 0.14t$	0.70689	$3 \text{ x } 10^{58}e^{-0.07t}$	0.70609	$2 \times 10^{308}t^{-134}$	0.7059
		Capacity, K, [MW]	$3 - 0.002K$	0.68518	$3e^{-0.001K}$	0.70364	$7.5174K^{-0.252}$	**0.7402**
	System	Time [yrs]	408.75-0.202t	0.61892	$3 \text{ x } 10^{43}e^{-0.049t}$	0.64518	$2 \text{ x } 10^{308}t^{-98.64}$	0.64503
		Capacity [MW]	4.8-0.0012K	0.35553	$4.7e^{-30{,}000K}$	0.37198	$9.6614K^{-0.168}$	**0.64578**
CdTe	Module	Time [yrs]	203.14-0.1t	0.63087	$9 \text{ x } 10^{108}e^{-0.125t}$	0.64533	$2 \text{ x } 10^{308}t^{-251.2}$	0.64546
		Capacity [MW]	0.956-0.0001K	0.54445	$0.9485e^{-20{,}000K}$	0.58129	$2.9833K^{-0.198}$	**0.68542**
	System	Time [yrs]	435.85-0.2163t	0.50238	$3 \text{ x } 10^{142}e^{-0.163t}$	0.59727	$2 \text{ x } 10^{308}t^{-327.7}$	0.5972
		Capacity [MW]	1.9011-0.0003K	0.60293	$1.9305e^{-20{,}000K}$	**0.69315**	$7.4906K^{-0.244}$	0.56686
mc-Si	Module	Time [yrs]	1048.4-0.5212t	**0.74066**	$8 \text{ x } 10^{107}e^{-0.123t}$	0.695	$2 \text{ x } 10^{308}t^{-247.2}$	0.69514
		Capacity [MW]	4.491-0.0002K	0.20224	$3.7204e^{-6\times10^5K}$	0.2735	$64.282K^{-0.402}$	0.71926
	System	Time [yrs]	971.01-0.4823t	**0.72411**	$2 \text{ x } 10^{89}e^{-0.102t}$	0.64764	$2 \text{ x } 10^{308}t^{-204.2}$	0.64783
		Capacity [MW]	5.1376-0.0002K	0.2396	$4.477e^{-5x10^5K}$	0.23413	$43.326K^{-0.319}$	0.63091
sc-Si	Module	Time [yrs]	1989.7-0.9904t	0.65217	$4 \text{ x } 10^{131}e^{-0.151t}$	0.83194	$2 \text{ x } 10^{308}t^{-301.5}$	0.83218
		Capacity [MW]	8.7869-0.0012K	0.32367	$7.8747e^{-20{,}000K}$	0.60843	$136.68K^{-0.48}$	**0.88126**
	System	Time [yrs]	748.96-0.3712t	**0.74086**	$3 \text{ x } 10^{78}e^{-0.089t}$	0.68112	$2 \text{ x } 10^{308}t^{-179.1}$	0.68088
		Capacity [MW]	5.5057-0.0002K	0.55372	$5.45e^{-6x10^5K}$	0.51489	$38.599K^{-0.279}$	0.69112

Model structure

The structure of the model used in the dynamic net energy analysis is outlined in Figure SS3. Boxes represent stocks, pipes with taps represent flows and blue arrows represent mathematical connections, e.g.

$$E_{net} = E_{gross} - E_{con} - E_{O\&M} - E_{dec} \tag{9}$$

Where E_{net} is *net power production*, E_{gross} is *gross power production*, E_{con} is *electricity to construction*, $E_{O\&M}$ is *electricity for O&M* and E_{dec} is *electricity for decommissioning*. Energy is consumed by PV capacity in the construction phase (both operation and maintenance and decommissioning energy requirements are assumed to be zero). Energy is produced by PV capacity in operation. Net annual energy production is gross annual energy production, less energy consumed in construction of new capacity.

Inputs to the model are the historical data for installed capacity [GW], initial cumulative electrical energy demand (CE_eD) per unit of capacity [kWh_e/W_p], the rate of decline of CE_eD per additional unit of installed capacity [$kWh_e/W_p/GW$] and the capacity factor [%]. The model is run from 2000 to 2025. Five year average growth rates (2005-2010) were used to extrapolate beyond 2010. Installed capacity and the capacity factor together define the gross power output [TWh/yr]. Capacity additions in each time step [GW/yr] and CE_eD in that year together define the power to construction [TWh/yr]. We assume a consruction time of 1 year for all new capacity. The gross power output less the power to construction define the net power output [TWh/yr].

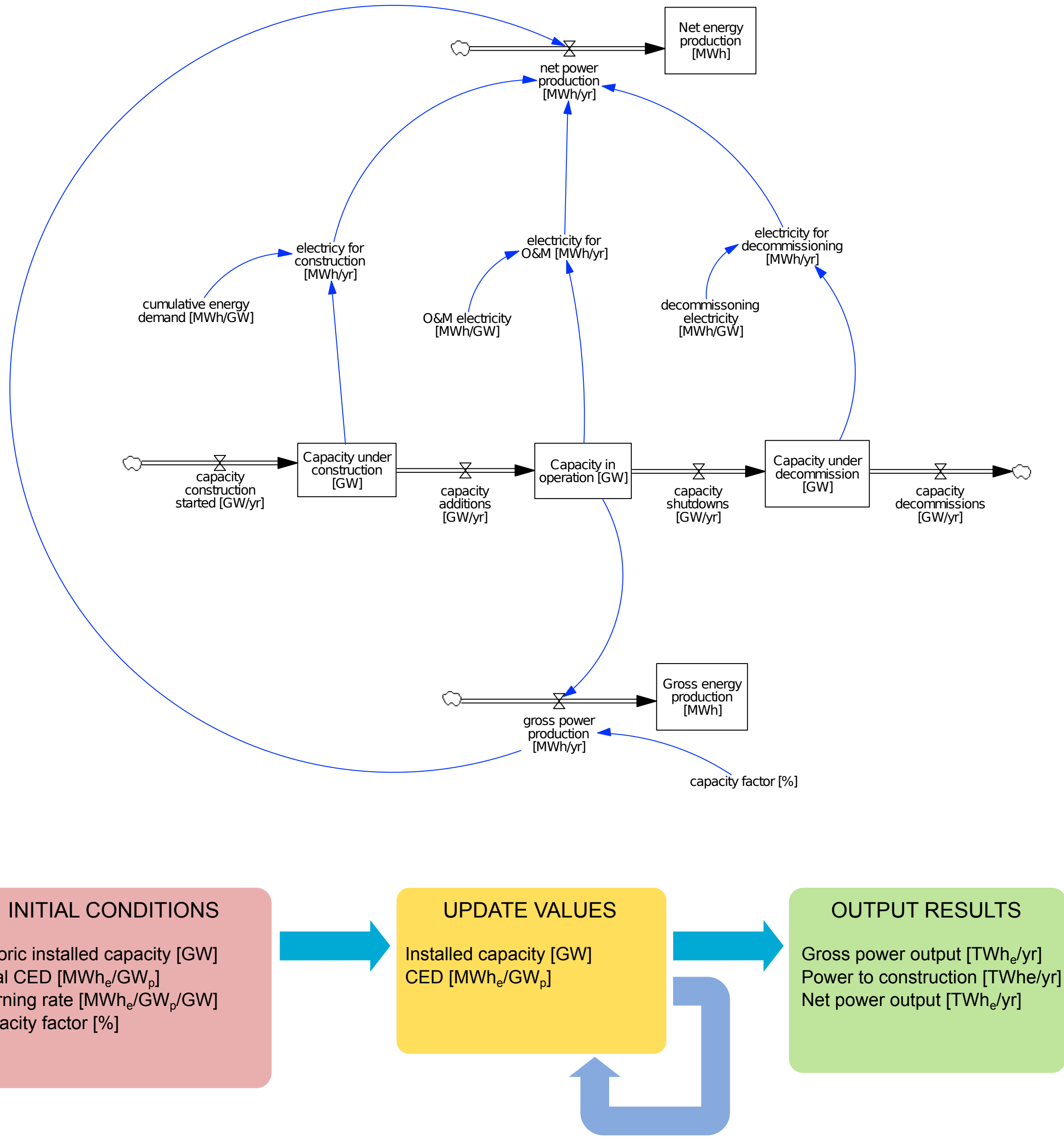

Figure S3: System dynamics diagram of basic model structure (top) and logical flow of model operation (bottom).

Operating & maintenance and disposal costs

The meta-analysis found that O&M and disposal costs are typically less than 5% of the full life-cycle costs of the PV system. O&M costs are distributed over the 25 year lifetime of the PV system. A sensitivity analysis was conducted around O&M and disposal costs. The result of this analysis found that inclusion of these costs had a less than 1% effect on the value of annual net energy production for the PV industry.

Monte Carlo simulation

Parameters for the sensitivity analysis were modeled assuming a normal distribution, details of which are specified in Table SS3.

Table S3: Parameters for Monte Carlo sensitivity analysis for variables 'initial CE_eD' [kWh_e/W_p] and 'capacity factor' [%].

Technology	**Initial CED** [$kWh/_e/W_p$]	**Learning rate** [dmnl]	**Growth rate 2010-2025** [%]	**Capacity factor** [%]
sc-Si	55.8 ± 10	0.18 ± 0.02	56 ± 2.8	12 ± 6
mc-Si	50.7 ± 10	0.20 ± 0.02	50 ± 2.5	12 ± 6
ribbon	12.9 ± 10	0.14 ± 0.02[a]	32 ± 1.6	12 ± 6
a-Si	26.7 ± 10	0.14 ± 0.02	48 ± 2.4	12 ± 6
CdTe	13.9 ± 10	0.15 ± 0.02	133 ± 66.5	12 ± 6
CIGS	12.9 ± 10	0.15 ± 0.02[b]	84 ± 42	12 ± 6

[a] assumed from a-Si
[b] assumed from CdTe

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Graphical TOC Entry