D1.3

A System Dynamics model on the diffusion of 1st and 2nd life PV in Germany

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1. LIST OF ABBREVIATIONS

Al	Aluminum
BOM	Bill of materials
BOS	Balance of systems
c-Si	Crystalline silicon
CAGR	Compound Annual Growth Rate
CAPEX	Capital expenditures
CDF	Cumulative distribution function
CE	Circular Economy
Cu	Copper
DfD	Design for disassembly
CO2	Carbon dioxide
EEG	Erneuerbare-Energien-Gesetz (Renewable Energy Sources Act)
ElektroG	Germany's Electrical and Electronic Equipment Act
EOL	End of Life
EPR	Extended Producer Responsibility
EU	European Union
EUR	Euro
EVA	Ethylene vinyl acetate
FITs	Feed-in-tariffs
GHG	Greenhouse gases
HSS	Home storage systems
IRENA	International Renewable Energy Agency
LC	Learning curve
LCOE	Levelized cost of electricity
Li-On	Lithium-ion
NPV	Net present value
O&M	Operation and maintenance
OPEX	Operational expenditures
PDF	Probability density function
PV	Photovoltaic
RES	Renewable energy sources
RUL	Remaining useful lifetime
Si	Silicon
STC	Standard test conditions
WACC	Weighted average cost of capital
WEEE	Waste from Electrical and Electronic Equipment

2. UNITS OF MEASURE

GW	gigawatts
GWh	gigawatt-hour
kWh	kilowatt-hour
kWp	kilowatt-peak
m	meters
m^2	square meters
MW	megawatts
t	tons
W	watts
Wp	watt-peaks

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5. INTRODUCTION

Solar PV have experienced strong market growth over the past two decades as a key vehicle for decarbonization of energy systems (see Figure 1). Although the exponential growth of PV installations, and their later recycling and waste generation, pose serious technical and environmental challenges, it also offers new value creation opportunities for key stakeholders along the PV value chain. One of such opportunities concerns the repair and reuse of decommissioned, failed or degraded PV modules for their redeployment as second-life products. It is estimated that up to 80% of the future PV waste stream will consist of modules with defects caused during production and transportation, or of infant failures taking place over the first four years of the panels' operational life, instead of products that have reached the end of their designed technical life (Weckend, Wade, & Heath, 2016). From that 80%, it is believed about 45% to 65% can be repaired or refurbished and commercialized as second-life panels (Tsanakas et al., 2019).

Current low reuse percentages of PV can be explained by several factors. First, although some online marketplaces for second-hand PV panel trading already provide refurbish services and certification, these frameworks do not deal with remaining lifetime expectancies or standardized, in-depth assessment of second-life modules. That is, technical and safety standards, which are needed to boost market confidence and adoption, remain rather informal, fragmented and superficial (Franco & Groesser, 2021). Second, not all used modules might qualify for repair or refurbish. Hence, while it makes economic sense to repair healthy, functional modules coming from replacement in strings or repowering, as well as modules with defects (e.g., diode failures), it might not be cost-efficient to do so for other types of module failures, including modules with junction box failures, fractured glass, cracked cells and snail trails. For the latter, the costs associated with reuse outweigh the costs of recycling/disposal, which makes the reuse case not worth pursuing. Finally, low volumes of available used modules also harm the use case for second-life PV since the resulting high inspection, transport, labor, and testing costs can sometimes exceed the cost of new, more efficient modules.

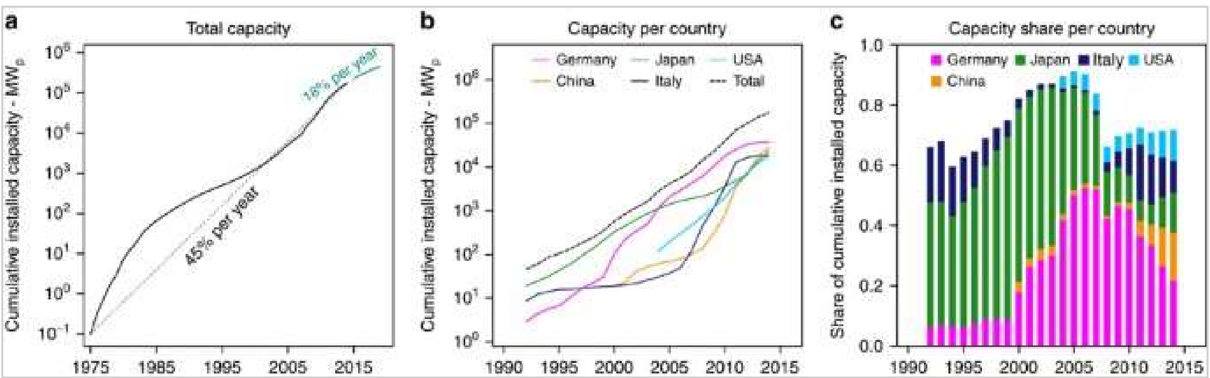

Figure 1 (a) Development of total cumulative installed PV capacity (all technologies), (b) Development of installed capacity per country for 5 main markets, (c) Development of total capacity share for five main markets. Source: Louwen, van Sark, Faaij, and Schropp (2016)

Although one could argue renewable energies are by default sustainable, challenges inherent to the management of end-of-life of PV systems remain. The International Renewable Energy Agency (IRENA) estimates that between 1.7-8 and 60-78 million tons of PV panel waste will have accumulated by 2030 and 2050, respectively. Hence, a look into the possibilities and frontiers for the deployment of 2nd life or used (as one of the Circular Economy strategies) PV is essential.

6. PROJECT DESCRIPTION

6.1. MODELING METHODOLOGY

This research proposes the development of a system dynamics simulation model to identify the dynamics created by the material/information flows involved in acceptance and diffusion of 1st and 2nd life PV in Germany. We chose system dynamics as the methodology to conduct this study for two reasons: (i) the growing importance and impact of solar PV technologies for the transition towards a more resilient, sustainable electricity industry globally, and (ii) the complex decision-making process associated with solar PV adoption, which offers an opportunity to investigate and quantify how economic, technical, and social factors affect household behavior. System dynamics is especially suitable for the latter.

System dynamics simulation models have been used in the past to portrait the diffusion of renewables including solar PV (Zapata, Castaneda, Franco, & Dyner, 2019), the role of feed-in tariffs (FIT) (Ahmad, Tahar, Muhammad-Sukki, Munir, & Rahim, 2015), solar PV investments and their diffusion in different country locations under different policy incentives (e.g., quotas, FITs, tax credits, subsidies, etc.) (Movilla, Miguel, & Blázquez, 2013), the energy mix of renewable energies (Aslani & Wong, 2014), the role of product-service systems in solar PV deployment (Schmidt-Costa, Uriona-Maldonado, & Possamai, 2019), and global trade in polysilicon (Sandor, Fulton, Engel-Cox, Peck, & Peterson, 2018). The software used to build this simulation model was Stella Architect[1].

A summary of the employed modeling process[2] is portrayed in Figure 2. Step one refers to gaining an understanding of the dynamic problem and the system it is embedded into. This first step can be achieved through multiple avenues including desk research, expert interviews, group facilitation sessions and many more. Step 1 is followed by a convergent activity whereby the dynamic problem is identified and refined in a statement. The approach continues with mapping and modeling (i.e., can be both quantitatively and/or qualitatively), followed by testing and validation for building model confidence. Although the points below are presented as a list, modeling (and any scientific activity) is iterative – a continuous process of formulating hypotheses, testing against data of all types, and revision of both formal and mental models.

[1] https://www.iseesystems.com/store/products/stella-architect.aspx
[2] https://www.systemdynamics.org/what-is-sd

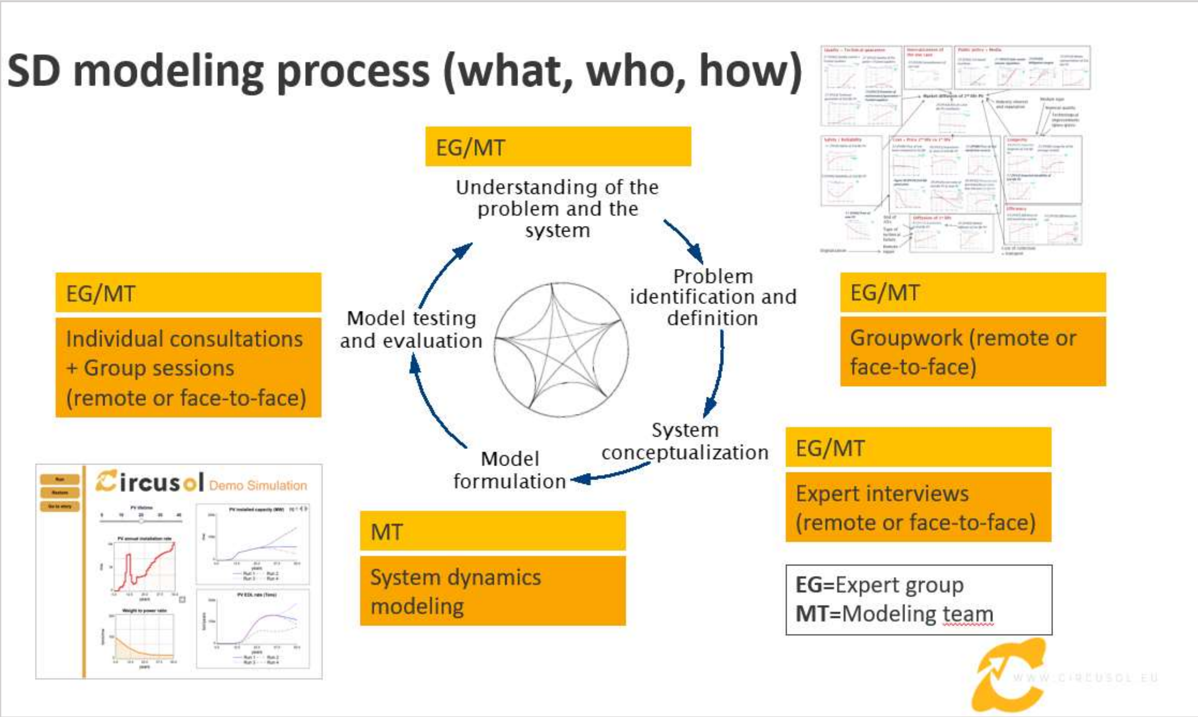

Figure 2 System dynamics modeling process

6.2. MODELING SESSIONS AND MODEL VALITDATION

We relied on group facilitation sessions, individual interviews and desk research in order to get acquainted with the functioning of the solar PV system and the different variables involved (see Figure 3). A detailed account of all interventions is displayed in Table 1. Important to highlight regarding information sources are the group model building sessions. These are made up by various convergent and divergent group activities and mainly used to support model conceptualization, the alignment of stakeholders' understanding of a complex system, and the formulation of effective policies (Hovmand et al., 2012). Figure 4 shows, for instance, a transcription of the group exercise performed in February 2020, where each participant was asked to draw the behavior over time of key variables in the European PV landscape. The so-called "reference modes" were accompanied by a verbal explanation in front of the group (the verbal account was transcribed verbatim).

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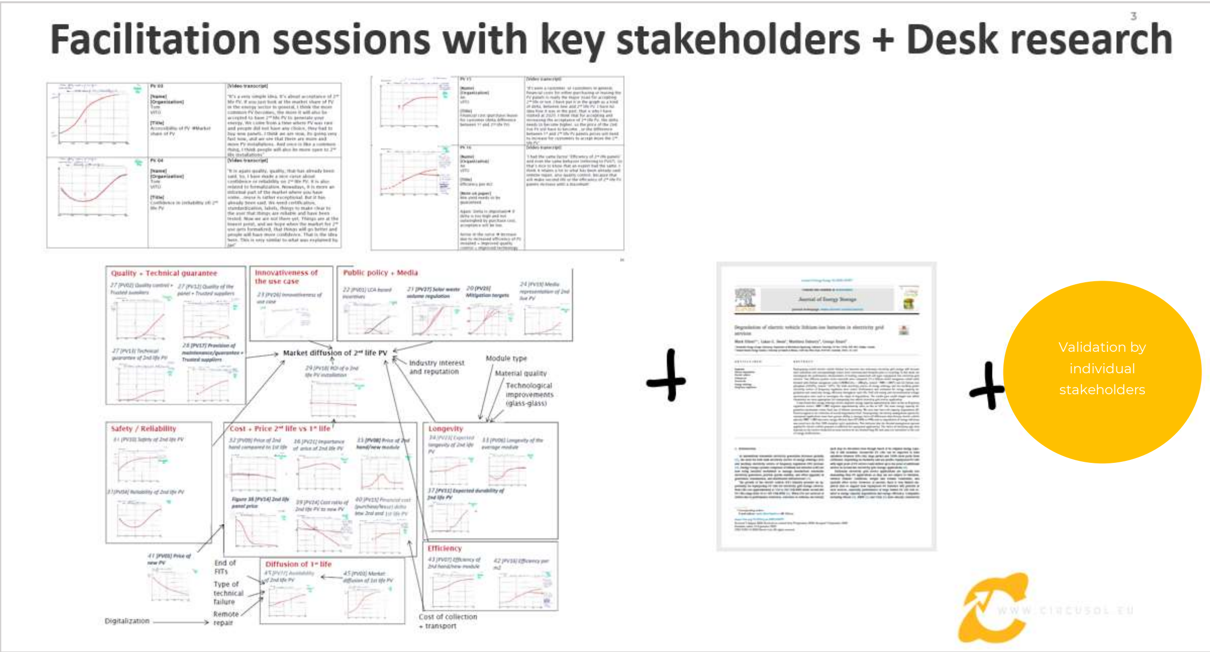


Figure 3 Sources for the conceptualization of the model structure

Table 1 Description of group interventions for this project

Date	Meeting type	Format	Duration (hours)	Goals	Products	Activity type	Number of participants
17.12.19	Group meeting	Online	1	Introduce project, methodology, concept model and next steps	Group exercise (3 questions answered live in Google Docs) + Results of coding responses	Divergent	9
21.01.20	Participant interview	Online	1	Model conceptualization (adoption of 2nd life PV)	Causal loop diagram + Simulation model	Divergent	1
22.01.20	Participant interview	Online	1	Model conceptualization (adoption of 2nd life PV)	Causal loop diagram + Simulation model	Divergent	1
18.02.20	Group meeting	Face-to-face (Consortium meeting)	1.45	Recap modelling process, validate current model structure and continue model conceptualization	Reference modes + Session transcript + Causal loop diagram + Simulation model	Divergent + Convergent	9

14.04.21	Group meeting	Online	1	Validate current model structure	Simulation model + Model slides	Convergent	10
20.04.22	Group meeting	Face-to-face (Consortium meeting)	0.5	Validate current model structure and presentation of results	Simulation model + Model slides	Convergent	10

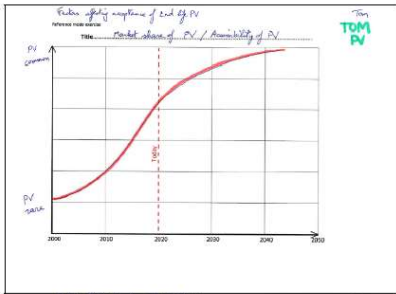
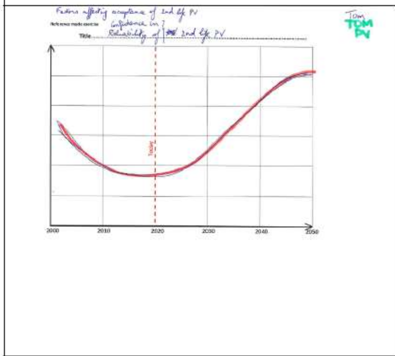
	PV 03 **[Name]** **[Organization]** Tom VITO **[Title]** Accessibility of PV →Market share of PV	**[Video transcript]** "It's a very simple idea. It's about acceptance of 2^{nd} life PV. If you just look at the market share of PV in the energy sector in general, I think the more common PV becomes, the more it will also be accepted to have 2^{nd} life PV to generate your energy. We come from a time where PV was rare and people did not have any choice, they had to buy new panels. I think we are now, its going very fast now, and we see that there are more and more PV installations. And once is like a common thing, I think people will also be more open to 2^{nd} life installations"
	PV 04 **[Name]** **[Organization]** Tom VITO **[Title]** Confidence in (reliability of) 2^{nd} life PV	**[Video transcript]** "It is again quality, quality, that has already been said. So, I have made a nice curve about confidence or reliability on 2^{nd} life PV. It is also related to formalization. Nowadays, it is more an informal part of the market where you have some…reuse is rather exceptional. But it has already been said. We need certification, standardization, labels, things to make clear to the user that things are reliable and have been tested. Now we are not there yet. Things are at the lowest point, and we hope when the market for 2^{nd} use gets formalized, that things will go better and people will have more confidence. That is the idea here. This is very similar to what was explained by Jan"

Figure 4 A closer look at the outcomes of the reference mode elicitation exercise

7. GERMANY AS A CASE STUDY

Germany was chosen as the case country for the simulation model introduced in this report, as it has one of the world's largest shares of PV in its electricity mix, with 707 gigawatts (GW) of cumulative installed capacity by the end of 2020. German PV development was especially strong between 2000 and 2012, period in which yearly installations soared (the same happened for the trajectory of solar cell production) (see Figure 5). From 2012, production decreased sharply, as the German PV manufacturing industry was greatly impacted by fierce competition from Chinese producers and the global economic crisis. A similar landscape was observed in the demand side, with a sharp decrease in yearly installations from 2012 onwards, due to the progressive reduction in FITs.

The installation of PV systems in Germany has been historically driven by government policy, as showcased by the results and ambitious targets introduced by the Renewable Energy Sources Act (in German "Erneuerbare Energien Gesetz" or EEG) in 2000[i]. This instrument, regarded as the central instrument in the expansion of renewable energy, guaranteed a feed-in-tariff (FIT) for the electricity generated from PV systems for a 20-year period and had a built-in annual reduction, which was adjusted over time to reflect rapid market growth of PV systems. This scheme was the main driver for the German solar boom in 2004 (Yu, Popiolek, & Geoffron, 2016).

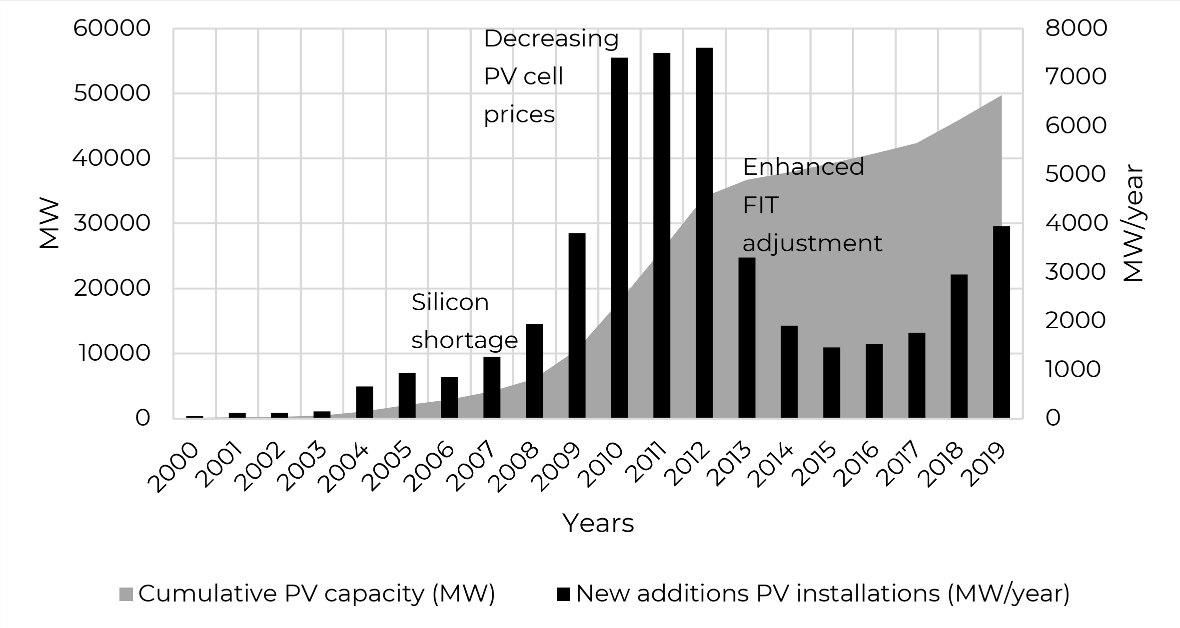


Figure 5 Development of Germany's cumulative installed capacity and yearly installations. Source: Authors' compilation (See Appendix)

Despite the increase in size of the PV plants in Germany, due to the falling energy prices, a large share of the German PV market is still made up of small-scale, residential PV systems (Hoppmann, Volland, Schmidt, & Hoffmann, 2014). Residential PV systems are therefore the focus of the model. In 2010, the federal government adopted the "Energy Concept" document, which sets out Germany's energy policy until 2050 and outlines measures to increase the share of renewable energy sources (RES) in electricity production (i.e., 30% by 2030, 45% by 2040 and 60% by 2050)[ii] and to decrease primary energy consumption (i.e., boost energy efficiency). In 2011, the concept document was complemented with a decision to phase out nuclear energy by 2022.

Table 2 Germany's climate and energy targets from the Energy Concept 2050. Taken from IEA (2021)

Target area	**2020**	**2030**	**2040**	**2050**
GHG emissions, compared with 1990	At least 40%	At least 55%	At least 70%	80%-95% (virtually GHG-neutral)
Primary energy consumption compared with 2008	-20%			-50%
Electricity consumption compared with 2008	-10%			-25%

Renewables in gross final energy consumption	18%	30%	45%	60%
Renewables in electricity consumption	35%	50-52.5%*	65%	80%
*The coalition government has set a new target of 65% renewables in electricity generation by 2030				

Expectations are for the amount of PV installed capacity to increase, as this is a core part of Germany's Energiewende or energy transition roadmap.

Table 3 Timeline of policy instruments in the German PV and battery systems. Sources: Figgener et al. (2020) and Vonsien and Madlener (2020)

Year	Policy or development
2000	Introduction of Renewable Energies Act (EEG) that guaranteed FITs for 20 years
2006	1st utility-scale (>10 MW) PV system installed in Germany after the 2004 revision of the German EEG, which for the first time made such systems eligible for a FIT
2010/2011	Further reduction of FITs. New energy policy "Energiewende" with 4 aims: (1) phase out nuclear in 2022, (2) reduction of GHG, (3) increase in the share of RES, (4) decrease in primary energy consumption
2012	Grid parity is achieved. Self-consumption is more economical than grid feed-in. Reasons: falling PV prices, falling FITs, high electricity prices
2013	Market incentive program launched by the federal government boosted the market penetration of HSS. From 2013-2015 the German government funded 55% of all new HSS installations. After 2015, the shares of funded projects decreased reaching a 5% minimum in 2018
2015	Li-on batteries gained significant market dominance. Before that, lead-acid batteries were more dominant
2021	The entitlement for the FITs for PV systems that were installed when the PV market emerged in 2000 will lapse

8. DESCRIPTION OF MODEL ASSUMPTIONS

The model´s time horizon is from the year 2000 up until 2050 and is being built according to the following general assumptions.

Table 4 Overview of main model assumptions

Assumption	Description	Source
PV system type	The model covers grid-connected PV systems only, since more than 98 percent of solar power systems in Germany are connected to the	Fraunhofer ISE (2020)

	decentralized low-voltage grid and generate solar power consumption	
PV technology	This study focuses on crystalline silicon solar cells based upon their popularity. Currently, the share of c-Si modules in the global market is reported to be around 90%	Fraunhofer ISE (2018)
PV system components	The PV system includes the solar panels and the balance of system (BOS) components (i.e., the inverters, electrical wiring, mounting structures and meters)	Authors' assumptions
PV market segments	Although the literature distinguishes among different PV system sizes (i.e., residential (<10 kWp), industrial (<1 MWp), which includes commercial <250 kWp and industrial <1000 kWp or 1 MW), and utility-scale (>1 MWp)), the model takes an aggregated approach to installed capacity where no segmentation is made.	Schmela (2020)
Business models	It is assumed in the base scenario that the capital costs of the PV system are paid upfront during the installation year and that the system starts producing electricity from the next year	Author's assumptions

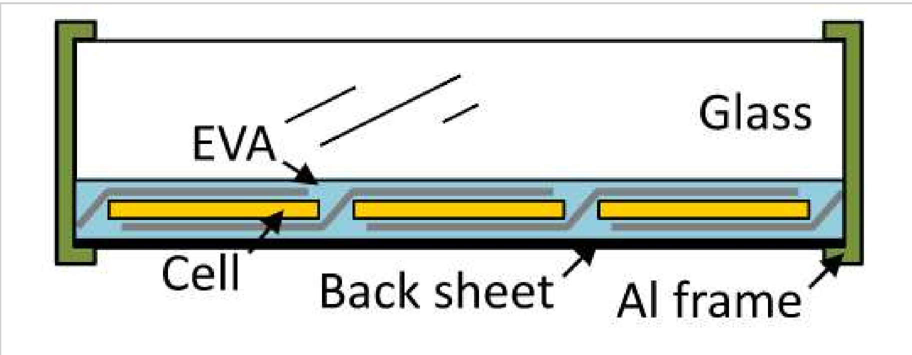


Figure 6 Schematic structure of today's most common Si modules. Source: Tao et al. (2020)

9. DESCRIPTION OF MODEL STRCUTURE AND MAIN PARAMETERS

The main model subsectors include: (i) the technical aspects of PV or the variables related to the calculation of the rated capacity of the average installed PV array, (ii) PV installed capacity, which accumulates, discriminating by age through an array configuration, the amount of MW of PV installed capacity in operation in the case study country, (iii) panel failures, which adds failed PV panels, calculated as a probability distribution along the panel´s lifetime, to the outflow of decommissioned PV, (iv) 2nd life PV supply that computes the volume of PV (based on the total decommission rate) available for repair and redeployment, (v) 2nd life PV performance, which calculates the remaining power of used

PV according to age, (vi) a financial subsector that calculates the levelized cost of electricity both for new and used PV, and (vii) a market diffusion subsector, mainly driven by the financial indicators described before, that moves households from grid consumers to prosumers (i.e., a consumer of electricity who also produces it, through a solar photovoltaic system. and can sell it back to the grid) using either new or used PV. Below a more detailed account of the main model subsectors and parameters.

9.1. TECHNICAL SUBSECTOR

9.1.1. SOLAR ENERGY GENERATION - NEW PV PANELS

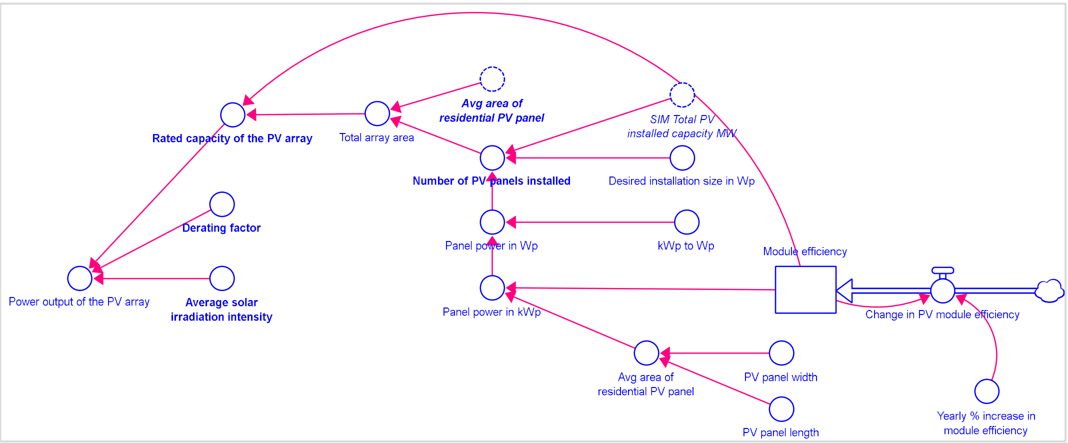


Figure 7 Model structure for solar energy generation with new panels

Figure 7 shows the model structure for calculating the power output of a PV array. First, the average residential panel size and the PV module efficiency are multiplied to calculate the rated capacity of a PV panel (variable "Panel power in kWp"). After this, based on the desired installation size in Wp and the calculated panel power, the number of PV panels installed for one PV system is calculated. Finally, to calculate the power of a PV array or system, we use a formulation similar to the one proposed by Ren, Mitchell, and Mo (2020):

$$P_{pv} = S * n * \beta * f_{pv} * D \qquad \text{Eq. 1}$$

Where:

P	Total power of the system [kWp]
S	Average residential panel size
n	Number of PV panels installed
β	PV module efficiency
f_{pv}	PV derating factor
D	Average incident solar irradiation

The subsections below provide details of most variables provided above:

9.1.1.1. PANEL SIZE

Average PV panel length was calculated at 1.559 m, whereas the panel width was calculated at 1.046 m. The multiplication of these two values results in a panel area of about 1.63 m^2.

9.1.1.2. SOLAR CELL EFFICIENCY

Solar cell nominal efficiency refers to the amount of solar energy that can be converted by solar cells into electricity[3]. High-efficiency photovoltaic panels therefore transform as much solar energy as possible into electrical energy, producing the same amount of electrical power on a smaller area since less material is needed. Of the three mainstream PV technologies (Franco & Groesser, 2021), monocrystalline silicon is the most expensive, but also achieves the highest conversion efficiency, whereas thin-film is cheaper, but reports the lowest efficiency (see Figure 8).

For crystalline PV modules, we calculated an average PV module efficiency increase of 1.4% per year, which we assume will continue until 2050. To obtain this average percentage, we used the Compound Annual Growth Rate (CAGR) formula[4], given the availability of incomplete data points (2010-2020) in the module efficiency data file provided by NREL[5]. For reference and comparison, an industry standard of 30% is assumed for 2050, including maximum theoretical thresholds in the laboratory and inevitable losses (Fraunhofer ISE, 2015). With the growth rate defined above, a similar efficiency number is obtained by the simulation in the year 2050.

Table 5 Historical average module efficiency data. Source https://www.nrel.gov/pv/module-efficiency.html

Year	Efficiency (%)	Year	Efficiency (%)
2000	12.6	2026	19.7
2001	12.9	2027	20
2002	13.1	2028	20.4
2003	13.3	2029	20.7
2004	13.5	2030	21.1
2005	13.8	2031	21.4
2006	14	2032	21.8
2007	14.2	2033	22.1
2008	14.5	2034	22.5
2009	14.7	2035	22.9
2010	15	2036	23.3

[3] More especifically, module efficiency (denoted by the symbol 'η') is the ratio of the solar power incident on the panel under Standard Test Conditions (STC) (i.e., vertical irradiance of 1000 watts per square meter, a cell temperature of 25°C, and an air mass of 1.5) divided by the module's power output under the same conditions. During operation, conditions are different from the standard ones and therefore, efficiency usually varies.

[4] The CAGR formula is as follows $CAGR = \frac{EV^{\frac{1}{n}}}{BV} - 1$ where EV refers to the ending value, BV to the beginning value, and n to the number of compounding periods.

[5] https://www.nrel.gov/pv/module-efficiency.html

2011	15.3	2037	23.7
2012	15.5	2038	24.1
2013	15.8	2039	24.5
2014	16.1	2040	24.9
2015	16.3	2041	25.3
2016	16.6	2042	25.8
2017	16.9	2043	26.2
2018	17.2	2044	26.7
2019	17.5	2045	27.1
2020	17.8	2046	27.6
2021	18.1	2047	28
2022	18.4	2048	28.5
2023	18.7	2049	29
2024	19	2050	29.5
2025	19.4		

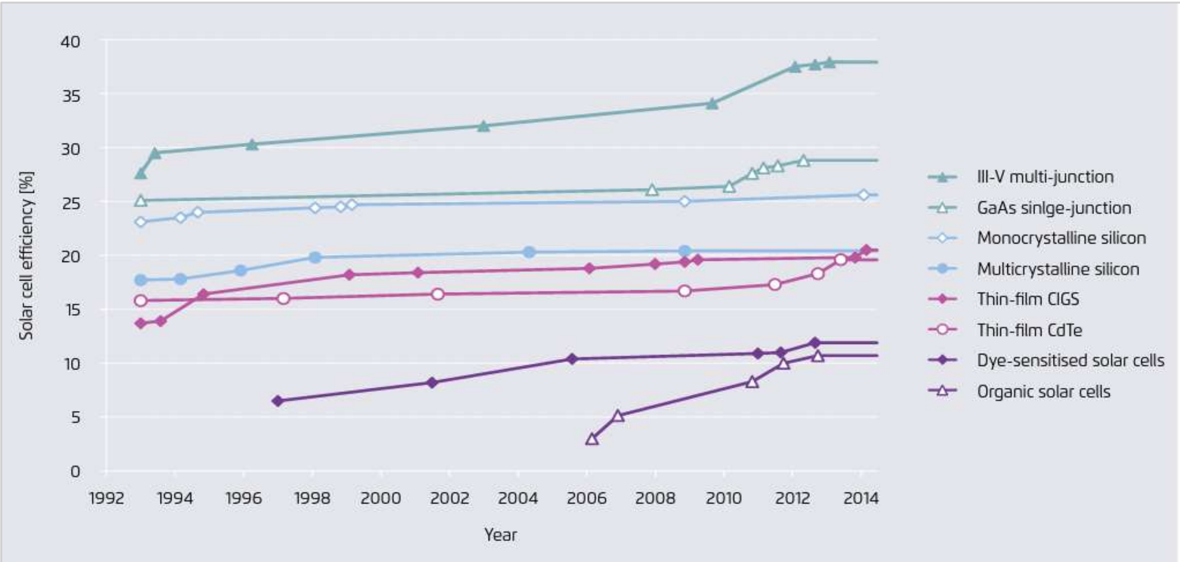


Figure 8 Historical development of solar cell efficiencies: High scores from the lab. Source: Fraunhofer ISE (2015)

9.1.1.3. DERATING FACTOR

The PV derating factor is a scaling factor that accounts for reduced output in real-world operating conditions compared to the standard conditions under which the panel was rated. More specifically, it refers to the efficiency losses caused by the different PV system components in different environments, including high temperature, clouding, aerosol optical depth, high dust concentration, snow, and shadow (Masrur et al., 2021). The overall derate factor is calculated as the multiplication all the individual derate values together. In the model, the Fraunhofer value of 0.85 is used (Fraunhofer ISE, 2020).

9.1.1.4. SOLAR IRRADITATION

Solar irradiation refers is measured in watt per square meter (W/m^2) and refers to the power per unit area received from the sun in the form of electromagnetic radiation. As evidenced in Figure 9, solar irradiation is low in northern Germany and high in southern Germany. According to Fraunhofer ISE (2020), the average annual sum of global irradiance in Germany between 1998 and 2018 was 1088 kWh/m^2/yr with a linear trend of +0.3% per year according to figures from the German Weather Service. Similar estimations yielded similar results, for example, when multiplying 3.06 hours of sun per day in Germany (on average) times 365 days, for a total of 1100 kWh/m^2/yr.

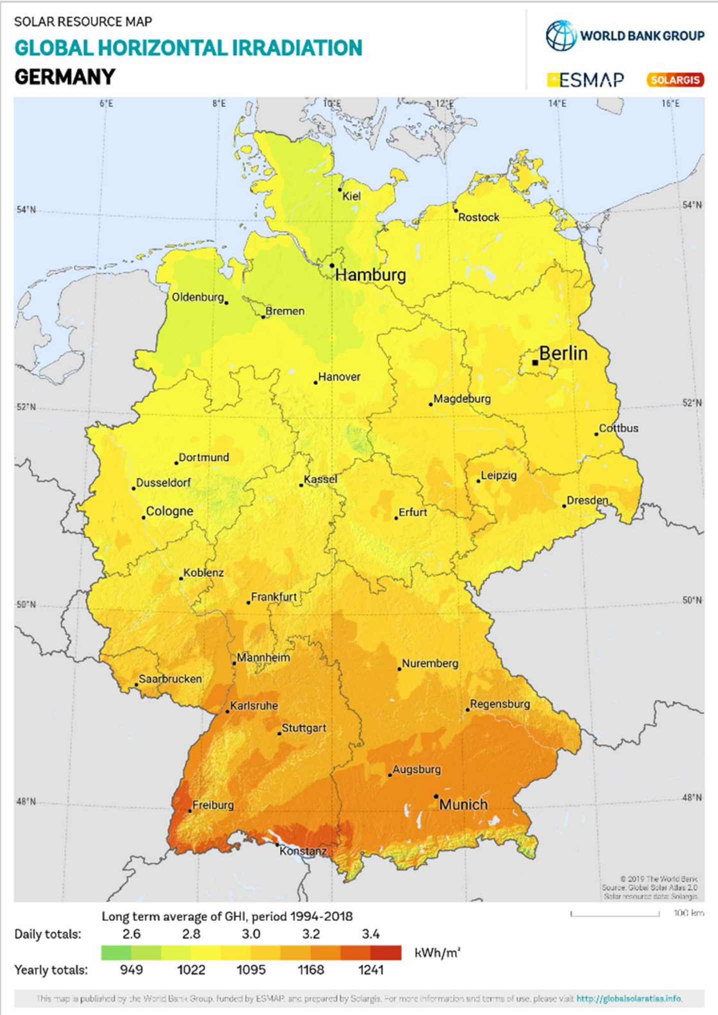


Figure 9 Global horizontal irradiation in Germany. Source: https://solargis.com/maps-and-gis-data/download/germany

9.1.1.5. FIELD POWER DEGRADATION RATE

The operating life of a PV module is highly determined by the amount it degrades over time. Jordan, Kurtz, VanSant, and Newmiller (2016) re-examined published data on photovoltaic degradation measurements and identified sampling bias in most of them, attributable to size and accuracy of the samples used. When accounting for sampling bias, the authors found the median degradation rate for x-Si technologies to be in the 0.5–

0.6%/year and a mean in the 0.8–0.9%/year range. Moreover, the authors address the issue of non-linearity in degradation rates for PV, an issue that has lately emerged in some publications. Upon closer scrutiny of the data, however, Jordan et al. (2016) also show the majority of modules exhibit a fairly linear decline, with only the worst performing modules showing wear-out non-linearities. When the switch for policy testing is not activated, we use a linear average degradation rate for the power output of PV modules of 0.8%/year.

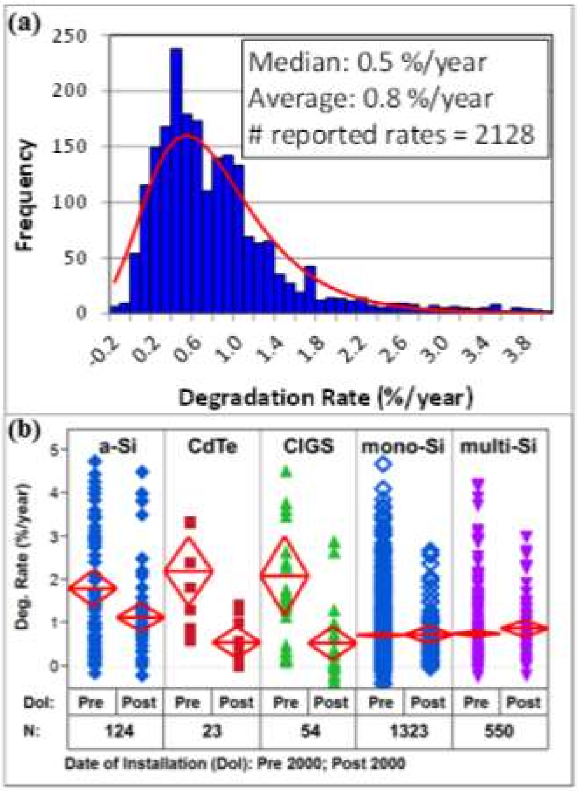


Figure 10 (a) Histogram of published degradation rates with an extreme value distribution fit (red line) and (b) Partitioned by technology and date of installation. Source Jordan et al. (2016)

9.1.2. INFLOWS AND OUTFLOWS TO PV INSTALLED CAPACITY

The stock of installed capacity in the model is fed by MW of PV installed per year and drained or emptied by the decommission PV rate. Depending on the amount and trajectory of MW installed per year, coupled with an estimated failure rate (see section below for more detail), the model can calculate decommissioned MW per year by age cohort (1 year-old panels, 2 years-old panels, etc.). To achieve this, there is built-in array structure in the stock (see Figure 11) governed by the variable “YearsHorizon.” This variable reflects the average lifetime duration of PV.

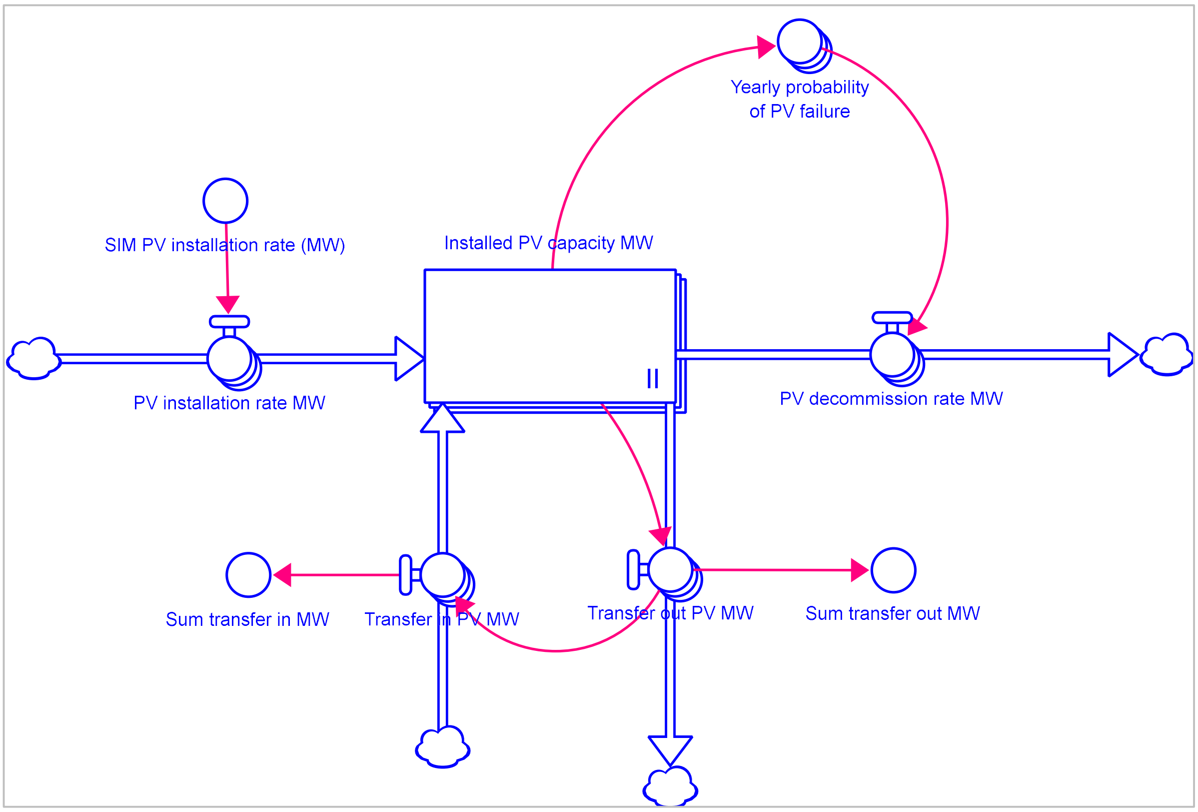


Figure 11 Model structure for the stock of PV installed capacity

9.1.2.1. DECOMMISSION RATE AND THE PROBABILITY OF LOSS/FAILURE

The exact time in which a PV module will fail cannot be precisely defined. Because of this uncertainty, the temporal evolution of failure/losses in a PV system has to be modeled by means of a probability distribution function (i.e., the Weibull distribution). The Weibull distribution is a well-known and commonly used model for analyzing the lifespan or reliability of a device (Kim and Park 2018), in this case for PV panels.

A failure in a PV module is defined as an effect that "degrades the module power, which is not reversed by normal operation, or creates a safety issue[6]" (IEA, 2014). The IEC 60050-191 defines failure as "the termination of the ability of an item to perform a required function" (Jordan, Silverman, Wohlgemuth, Kurtz, & VanSant, 2017). As opposed to field degradation, failures in PV are not considered to be caused by mishandling or the local environment. The table below lists some of the most common causes of failures reported throughout the PV lifetime.

Table 6 Infant, midlife and wear-out failures of PV modules (wafer-based crystalline modules). Taken from IEA (2014) and Weckend, Wade, and Heath (2016)

Lifetime period	Description	Failure type

[6] A safety failure

Infant failures	Occurring up to four years after installation (average two years)	• Light-induced power degradation (LID) after installation • j-box failure • Glass breakage • Defective cell interconnect • Loose frame • Delamination
Midlife-failures	Occurring about five to eleven years after installation	• Power-induced degradation (PID) • Diode failure • Cell-interconnect breakage • Degradation of the anti-reflective coating of the glass • Discoloration of the ethylene vinyl acetate • Delamination • Cracked cell isolation
Wear-out failures	Occurring about 12 years after installation until the assumed end-of life	• Delamination • Cracked cell isolation • Discoloration • Severe corrosion of cells and interconnectors

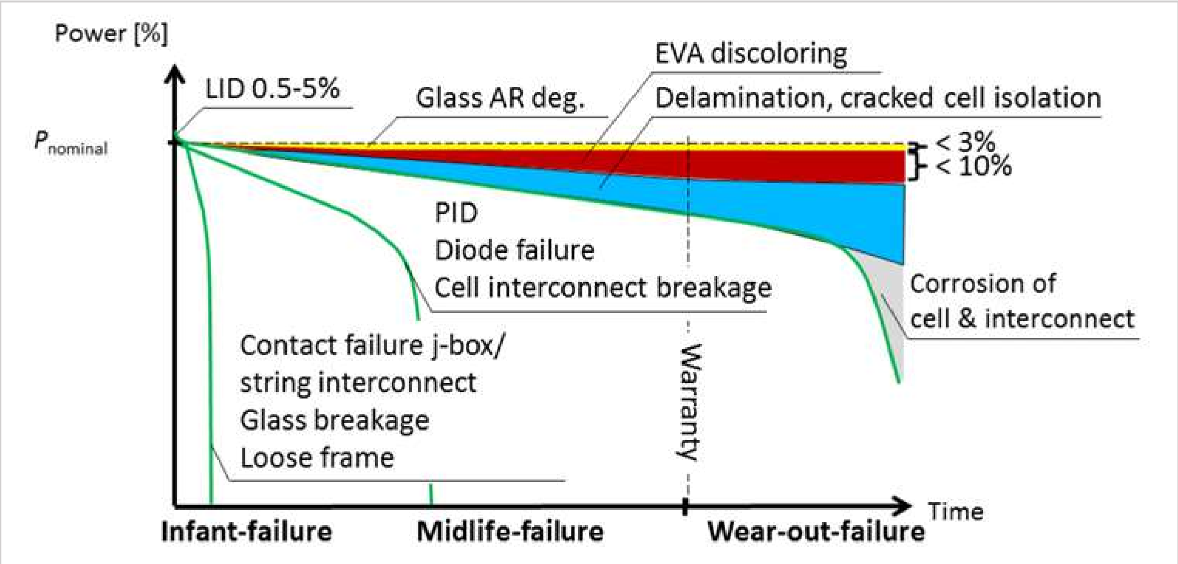


Figure 12 Three typical failure scenarios throughout PV modules' lifetime (wafer-based crystalline modules). Taken from IEA (2014)

THE WEIBULL DISTRUBTION FOR PV FAILURE RATES

The lifespan distribution or the loss/failure distribution varies according to a shape parameter alpha (α), which illustrates how the failure rate of a device changes according to time. A shape parameter greater than 1 means the failure rate increases with time, which is generally the case. When the shape parameter is between 3 and 4, the probability of failure of a device is distributed along a bell curve (also known as the probability distribution function or PDF). The PDF is associated with the probability of a continuous random variable falling within a specific interval. The equation for the PDF reads as follows:

$$f(t) = \alpha\lambda(\lambda t)^{\alpha-1}e^{-(\lambda t)^{\alpha}} \quad \textbf{Eq. 2}$$

Where:

t	Time in years
1/λ	Mean lifespan
α	Shape factor controlling the S shape of the Weibull curve

In the model structure, the equation above is translated as follows (see also Figure 13). [For reference, the formulation refers to the regular loss scenario]

Probability density function regular loss = Alpha_shape_factor_PV_regular_loss_scenario(1/Used_1st_PV_lifetime)*(1/Used_1st_PV_lifetime*YearsHorizon)^(Alpha_shape_factor_PV_regular_loss_scenario-1)*EXP(**"PV_regular_loss_(t/T)^a"**[YearsHorizon])* **Eq. 3**

PV regular loss (t/T)^a*=(-(YearsHorizon/ Used_1st_PV_lifetime)^ Alpha_shape_factor_PV_regular_loss_scenario)* **Eq. 4**

The plotting of the PDF serves a graphical purpose only, since it is not used as input for any other variable in the simulation. Instead, one of its factors (see Eq. 4) is used to calculate a cumulative distribution function or CDF, which represents the integral of the probability density function. In the simulation, two parameters are used to define the CDF of the Weibull function for an early loss scenario and regular loss scenario: (i) the shape parameter (α) and (ii) the mean lifespan (1/λ). The probability of loss is therefore dictated by the following formula:

$$F(t) = \int_0^t f(x)dx = 1 - e^{-(\lambda t)^{\alpha}} \quad \textbf{Eq. 5}$$

Where:

t	Time in years
1/λ	Average lifetime
α	Shape factor controlling the S shape of the Weibull curve

In the model, Eq. 5 reads as follows (for a regular loss scenario as reference):

1- (EXP ("PV_regular_loss_(t/T)^a"[YearsHorizon])) **Eq. 6**

To calculate the decommission rate of PV, the probability of failure is multiplied by the installed capacity in MW for a given year. The choice of regular or early loss scenario is activated/deactivated in the model by means of a switch that has a value of 0 when the regular loss scenario is activated and 1 when the early loss scenario is activated. The yearly probability of failure is therefore governed by Eq. 7:

IF SWITCH_Early_loss_scenario=1 THEN Installed_PV_capacity_MW[YearsHorizon] CDF_PV_failure_early_loss_scenario[YearsHorizon] ELSE Installed_PV_capacity_MW[YearsHorizon]* CDF_PV_failure_regular_loss_scenario[YearsHorizon]* **Eq. 7**

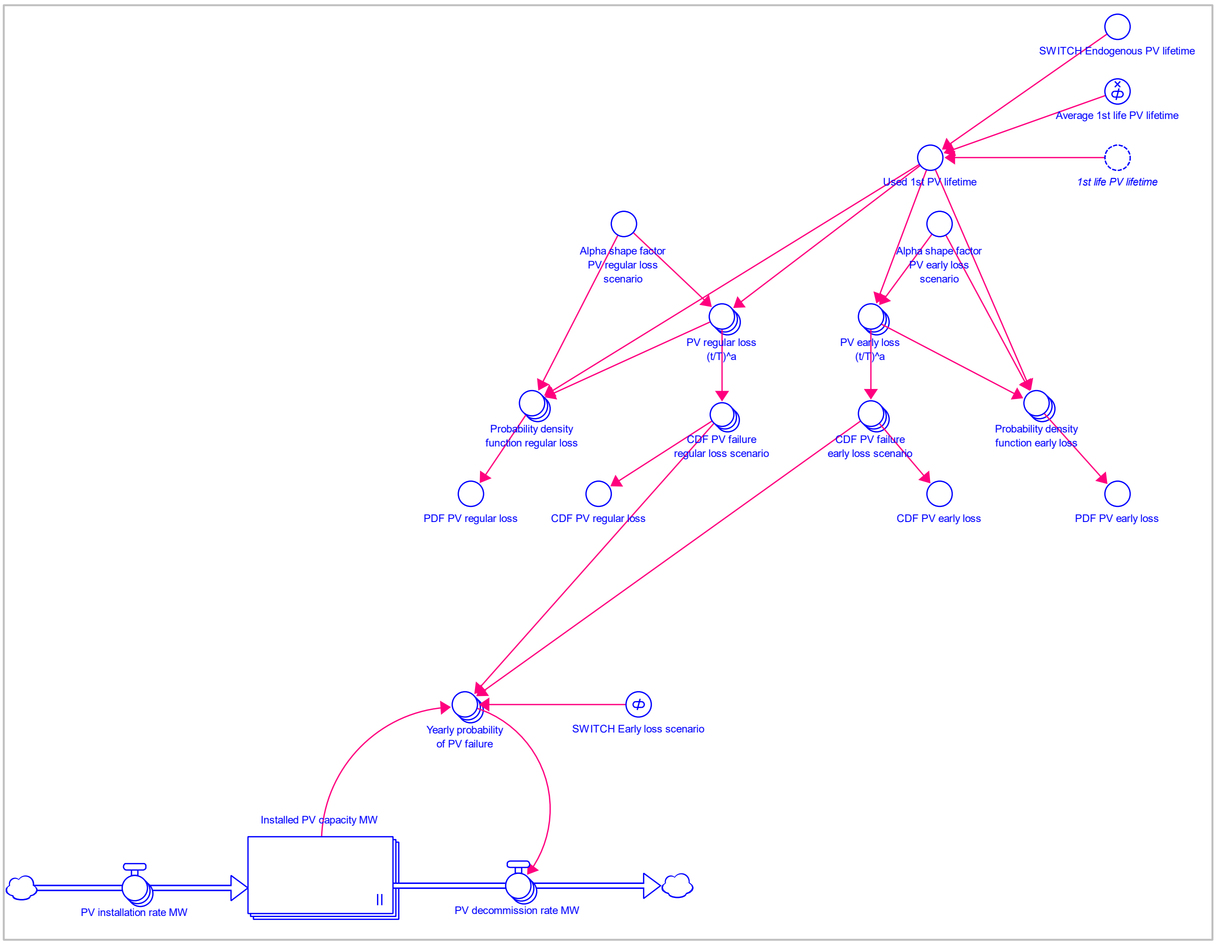


Figure 13 Model structure for calculating the decommission rate

According to a literature review published by Weckend et al. (2016), the alpha shape factor in in the regular-loss scenario is assumed to be 5.3759, whereas the alpha shape factor for the early-loss scenario is set to 2.4928[7]. These values, confirmed also by Kim and Park (2018), are used in the model.

[7] For more details on the assumptions for regular and early-loss scenarios, refer to page 30 of Weckend et al. (2016)

Source	Shape Parameter			Explanation
	Lower	Upper	Median	
Collins et al. [35]		1.9055		- 5-year (2003–2007) field data in Arizona, USA - crystalline module - in addition to module, shape factors for other parts of BOS
Kuitche [31]	3.3	8.7488	5.3759	- at least 8-year and 4 different climate (hot-dry, cold, hot-humid) field data in Arizona, USA - c-Si cell
Laronde et al. [30]	2.6	7.56	5.03	- literature data and a petri network - c-Si module
Dietrich et al. [36]		7		- fracture test data - mono-Si wafer
Kumar and Sarkar [28]	9.982	14.41		- stress accelerated life test data - two sets of PV panel (no specification of PV technology)
EC [33]		3.5		- no specification
Tont and Tont [37]		1.0739		- use data of Maish et al. (1997); Maish et al. (1997)'s data: 400 grid-connected residential PV (2–4 kW) installed between 1993 and 1995 in Sacramento, USA - no specification of installed PV

Figure 14 Summary of shape parameters for PV modules in existing studies. Source: Kim and Park (2018)

9.1.2.2. ESTIMATING PANEL WASTE IN TONS

To estimate PV panel waste, a co-flow structure is introduced in the model to convert the installation/decommission rate in MW to a unit of mass (i.e., installation/decommission rate in tonnes). To achieve this conversion, a variable named "Weight to power ratio" (t/MW) is introduced. The weight to power ratio accounts for the relationship between panel efficiency on panel weight, or in other words, the extent to which more efficient panels result in lighter panels over time. Using the data gathered by IRENA in its report from 2016 "End-of-life management: Solar Photovoltaic Panels" (Weckend et al., 2016)[8], a measure of t/MW over the simulated time horizon was used to convert MW of installed capacity into mass.

[8] In the report, an "average ratio of mass of PV per unit (t/MW) was calculated by averaging available data on panel weight and nominal power. For past PV panel production, the nominal power and weight of representative PV panels was averaged from leading manufacturers over five-year intervals"

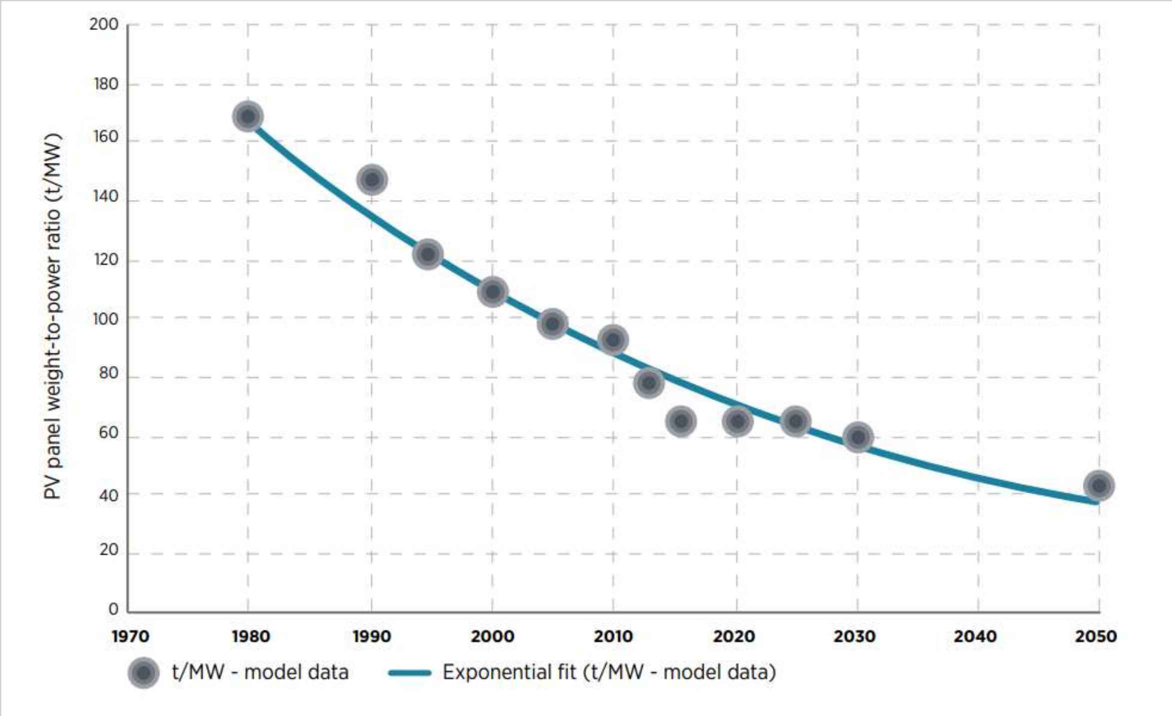


Figure 15 Exponential curve fit projection of PV panel weight-to-power ratio. Source: Weckend et al. (2016)

Most waste is typically generated during four primary life cycle phases of any given PV panel (Weckend et al., 2016).

Table 7 Reference waste % across PV lifetime stages. Source: Weckend et al. (2016)

Manufacturing	Transportation and installation	Use after installation			EOL
		Infant	Midlife	Wear-out	
N/A in the IRENA report	0.5% (we take this value for the section on evaluating Policy package 1)	0.5%	2%	4%	N/A in the IRENA report

9.1.3. USED PV PANELS

From a CE perspective, besides to PV recycling, onsite or off-site repair of failed module components is gaining increasing interest and enables the establishment of entire second-life PV systems (Tsanakas et al., 2019). Although not all PV failure types can be economically repaired (this has been already shown by other work packages within the CIRCUSOL Consortium), repair/refurbishment of PV modules are most likely to be applied to the following cases: (i) defective frames and mounting clamps; (ii) faulty bypass diodes and defective wire connectors in junction boxes; (iii) certain PV backsheet defects; and (iv) potential-induced degradation (PID) (Tsanakas et al., 2019).

In the process of deploying second-life PV modules, besides the repair aspect, addressing the question of module age and remaining power is important. It is widely acknowledged that during PV modules' operational lifetime, physical degradation inevitably occurs. Therefore, and to calculate the financial attractiveness for used PV panels, a calculation for the remaining power capacity of these panels is introduced.

9.1.3.1. REMAINING POWER CAPACITY OF 2ND LIFE PV

The remaining power output of a used module is calculated by dividing the panel power in its year of manufacturing, factoring in the its corresponding degradation until the decommissioned year, by the power output of a new module manufactured in the current year of the simulation (Rajagopalan et al., 2021). Hence:

$$P^u = a * P^n \quad \text{Eq. 8}$$

Where:

P	Total power of the system [kWp]
a	Remaining power share of prematurely decommissioned panels compared to new panels

For example, assuming the time step in the simulation is the year 2020 and we want to calculate the remaining power of a panel manufactured in 2010 and decommissioned at year 10, the following formula would be used:

$$Remaining\ power\ panel\ 2010 = \frac{Panel\ power\ year\ 2010 * Field\ degradation\ rate}{Panel\ power\ yr\ 2020} \quad \text{Eq. 9}$$

Remember from previous sections, that the power (or the rated capacity) of the PV panel depends on the average area of the residential panels multiplied by panel efficiency (refer to section 9.1.1). By default, then, the variable "Panel power in Wp" will gradually increase throughout the simulation. The main model equations in the formulation shown below are as follows:

Identity matrix= IF TIME = YearsHorizon -2 THEN 1 ELSE 0 **Eq. 10**

*Panel power in Wp identity= Panel_power_in_Wp*Identity_matrix[TIME+2]* **Eq. 11**

Remaining power share per cohort 2nd life PV= SAFEDIV(Remaining_panel_power_in_Wp, Panel_power_in_Wp_identity) **Eq. 12**

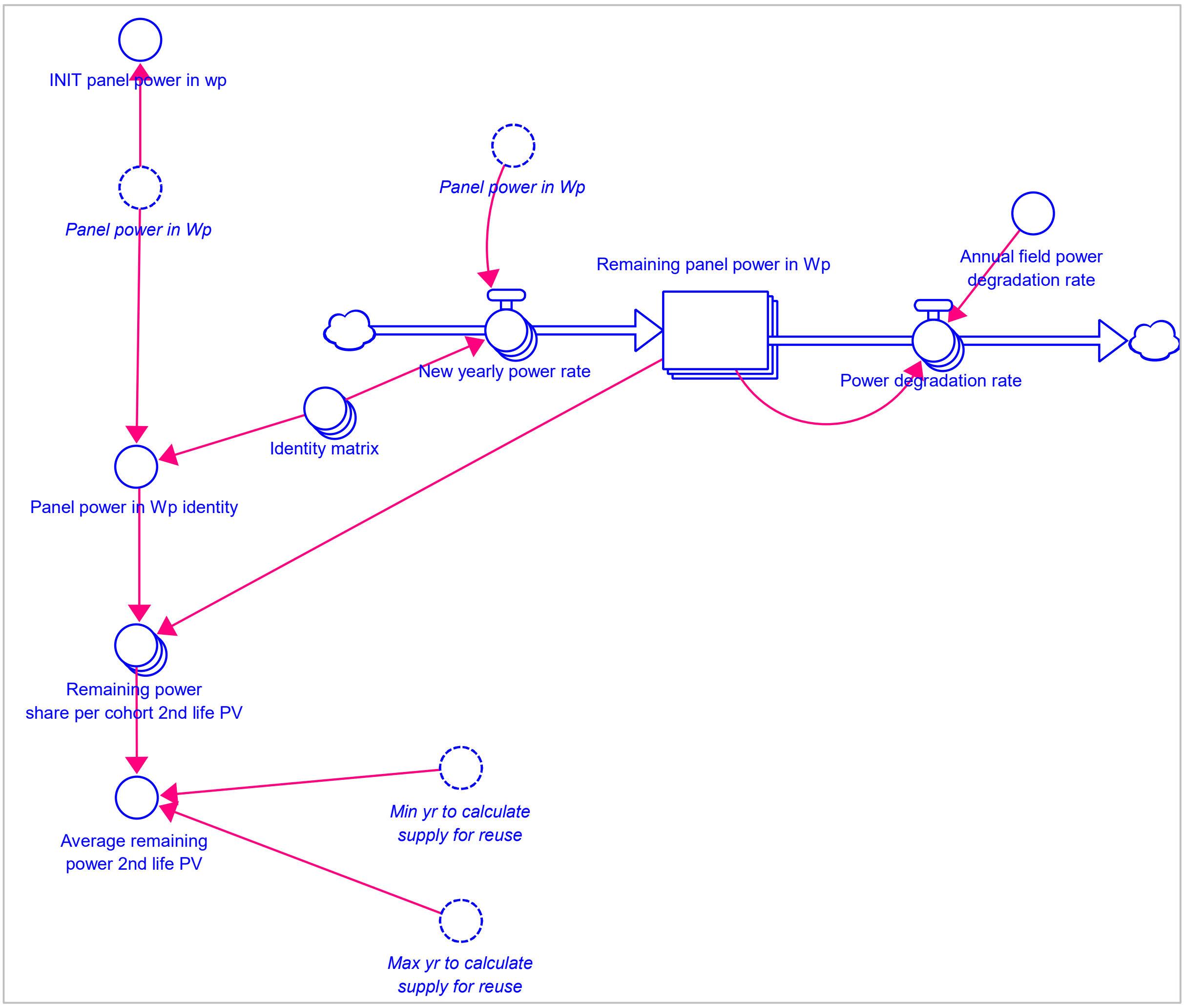


Figure 16 Model structure for the calculation of the remaining panel power for 2nd life PV

The stock "Remaining panel power in Wp" is an arrayed[9] component in the model that reflects the calculated remaining power of panels from each age cohort in the simulation (1, 2, 3-year old panels, etc.). It is fed by the panel power of the corresponding simulation time step and it is emptied by the calculated "Power degradation rate":

Power degradation rate = **Eq. 13**
*Annual_field_power_degradation_rate*Remaining_panel_power_in_Wp*

The variable "Identity matrix" in Eq. 10 serves as a dummy variable that uses values from past time steps to be used for calculations in the current time step. The variable "Remaining power share per cohort 2nd life PV" calculates the power left in the stock after degradation and then the variable "Average remaining power 2nd life PV" resembles the formulation in Eq. 9.

[9] For a more detailed overview of arrays in System Dynamics models visit: https://www.iseesystems.com/resources/help/v2/#03-BuildingModels/Working_With_Arrays/Overview_Working_With_Arrays.htm%3FTocPath%3DBuilding%2520models%7CWorking%2520with%2520arrays%7C_____0

9.2. FINANCIAL SUBSECTOR

9.2.1. LEARNING CURVE FOR PV MODULES AND INVERTERS

The capital investment (CAPEX) of a PV system consists primarily of the PV module cost and the Balance of System (BOS) costs. The operational costs (OPEX) correspond to the maintenance costs. For the year 2015, a breakdown of the costs for PV installations looked like this:

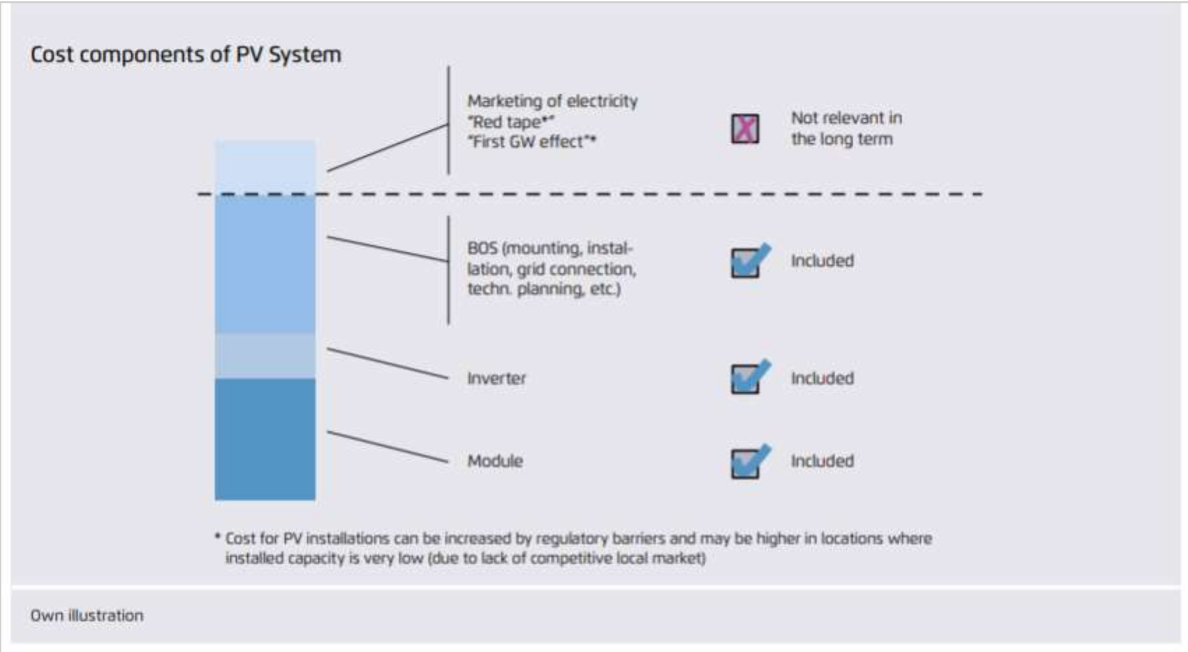


Figure 17 Breakdown of PV system costs. Source: Fraunhofer ISE (2015)

For plotting the initial value of the price stock for the year 2000, we use reference prices distributed as follows. From 2000 onwards, the prices for modules, inverter and BOS and were calculated endogenously based on learning rates.

Table 8 Breakdown of PV system costs for the year 2000

Module	55%
Inverter	11%
Area-related BoS (e.g., mounting system, cables and installation)	23%
Other BOS	11%

9.2.1.1. LEARNING CURVE FOR SOLAR PV MODULES

The cost of photovoltaic installations has changed dramatically over the past two decades. PV module costs are mainly determined by raw material costs (in our case the cost of silicon), cell manufacturing costs and module assembly costs. At the beginning of the 2000s, module costs accounted for the biggest share of the total capital costs of PV systems. Nowadays, however, BoS costs exhibit the largest share in PV capital investment.

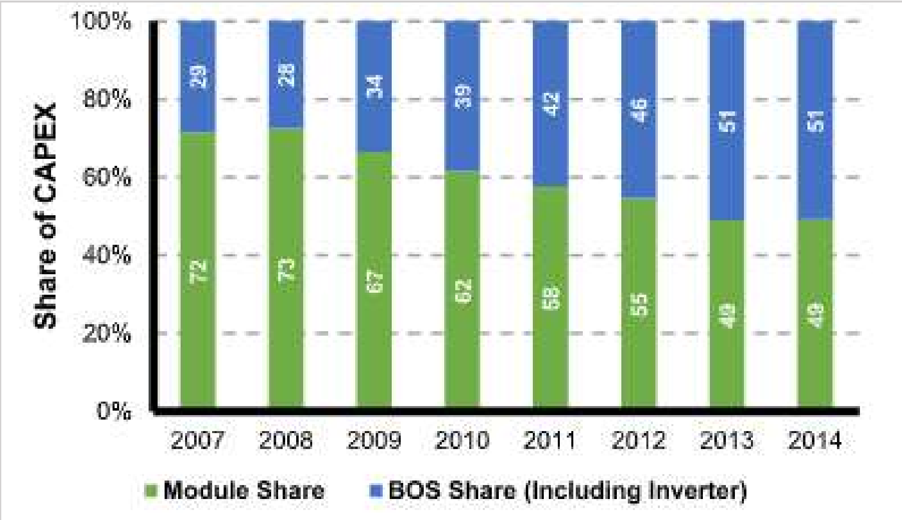


Figure 18 Share of modules and BOS (including inverter) in the average price of rooftop solar installations in Germany. Taken from: Elshurafa, Albardi, Bigerna, and Bollino (2018)

Fraunhofer ISE (2015) reports historical learning rates[10] between 81% and 77% for PV modules[11]. For this study, we use an average learning curve (LC)[12] 79.1%. This means that each time the cumulative production doubled, the price of PV panels went down by 20.9% (i.e., this is referred as the progress ratio or PR).

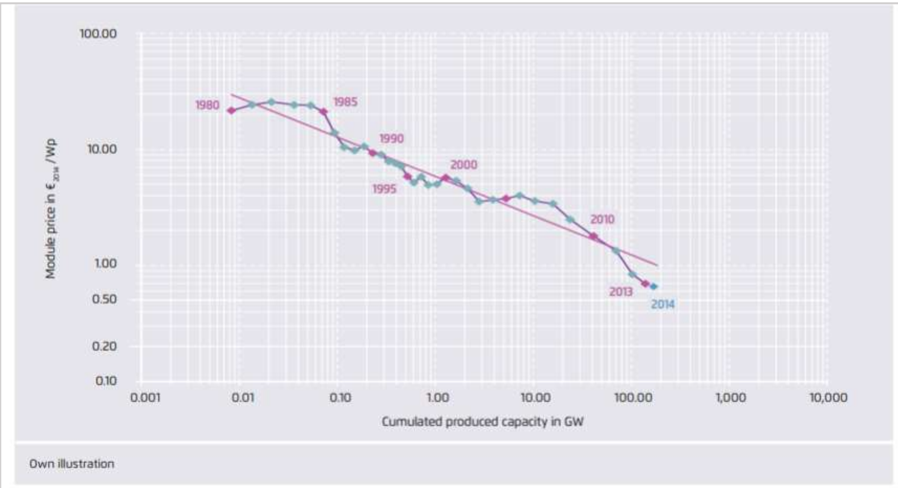


Figure 19 Historical price experience curve for modules since 1980. Source: Fraunhofer ISE (2015)

In the model, the future price of PV modules is calculated from cumulative installation volumes. Mathematically, the LC can be expressed as (Elshurafa et al., 2018):

$$C_Q = C_1 * Q^{-\beta} \quad \textbf{Eq. 14}$$

Where:

C_Q	Marginal cost of producing the Qth unit

[10] The starting year for the PV experience curve in Fraunhofer's analysis was 1980
[11] See also Louwen et al. (2016)
[12] Also referred to as learning rate or experience curve

C_1	Cost of producing the first unit
Q	Cumulative quantity produced
β	Learning coefficient (main parameter)

The corresponding LC would be then equal to:

$$LC = 2^{(-\beta)} \qquad \text{Eq. 15}$$

Since the LC is reported, the model calculates the beta learning coefficient based as follows:

$$\beta = \frac{\log(LC)}{\log(2)} \qquad \text{Eq. 16}$$

Finally, to calculate the module price at each time step in the simulation, we use the following equation (similar to Eq. 14):

$$PV\ module\ price = Actual\ vs\ reference\ cumulative\ PV\ capacity^{-\beta} \qquad \text{Eq. 17}$$

9.2.1.2. LEARNING CURVE FOR BOS

Costs associated to the BoS include the inverter, mounting structures, cabling, transformers and other electrical components, grid connection, infrastructure, installation work, planning and documentation. For the case of Germany, BoS costs accounted for about 60% of total costs in 2020. For utility-scale installations BOS account for about 40% of the cost (IRENA, 2012).

A further differentiation is made between non-area related BOS and area-related BOS. The non-area related BOS is the inverter, whereas the area-related BOS include the rest of the costs. Although some studies use one learning rate for the BoS costs (including the inverter), we decided to report them separately, that is, one learning rate only for the inverter and another % decrease for the cost of other BoS elements. This was based on the fact that area-related BOS costs play a big role in the financial calculations for second-life PV.

Non-area related BoS: Inverter

Just as PV modules, inverters have showcased a steep learning curve with costs going down from over 1 EUR/Wp in 1990 to almost 0.10 EUR/Wp 2014 (Fraunhofer ISE, 2015). Improved power semiconductors and new circuit topologies are the reason for the price reductions. In the simulation, the LR for inverters is set to 18.9%.

Area-related BoS

"Since there is no long-term historical price data available for the BOS (balance of system) components and unlike modules and inverters, non-technology cost such as planning, licensing and local infrastructure are included, this approach seems less suitable to project future BOS costs." We therefore used a % decrease that calculates area-related BOS prices based on the previous year. The selected average for costs including installation, mounting structure, DC cabling, grid connection, infrastructure, planning and documentation and transformer are based on the average reduction % provided in Fraunhofer ISE (2015).

Table 9 Summary of learning rates used to calculate capital costs of PV systems throughout the simulation

Learning rate	Value	Source
Learning rate modules	20.1%	Fraunhofer ISE (2015)
Learning rate inverter	18.9%	Fraunhofer ISE (2015)
% decrease for other BoS components	39% reduction by 2050	Fraunhofer ISE (2015)

9.3. THE LEVELIZED COST OF ELECTRICITY (LCOE)

According to Figgener et al. (2020), German consumers install new PV systems motivated by their personal contribution to the energy system transformation, and also largely driven by financial factors such as feed-in tariffs and related economic profitability. To compare the financial preferability of new and second-life PV, we use the Levelized Cost of Electricity (LCOE) method. The LCOE of photovoltaic PV depends largely on the following parameters: CAPEX or standard investment costs, OPEX or operating costs, average solar irradiation, installation lifetime, and financial conditions.

More especifically, the LCOE is calculated by comparing all costs incurred over the lifetime of a PV installation (i.e., both fixed and variable costs for the operation of the PV site) and the total amount of energy generated (see section on technical parameters). The calculation is based on the Net Present Value (NPV) method, whereby the investment expenses, as well as the flows of revenues and expenditures during the installation's lifetime, are discounted related to a discount rate and divided by the present value of electricity generation.

For calculating the LCOE of new PV installations, the following formula applies:

$$LCOE = \frac{CAPEX\ (PV) + CAPEX\ (BOS) + OPEX}{Total\ electricity\ production} \quad \textbf{Eq. 18}$$

$$LCOE = \frac{Price_{PV} + Price_{BOS} + \sum_{t=1}^{N} \frac{OPEX}{1 + WACC_{nom}}^{t}}{\sum_{t=1}^{N} Yield * \frac{(1 - Degradation)^t}{(1 + WACC_{real})^t}} \quad \textbf{Eq. 19}$$

Where:

t	Time [years]
N	Economic lifetime of the system [years]

$Price_{PV}$	CAPEX for PV panels at t_0 [EUR/kWp]
$Price_{BOS}$	CAPEX for BOS components at t_0 [EUR/kWp]
OPEX	Operational expenses (operations and maintenance) over the lifetime of the system [EUR/year/kWp]
Yield	Initial system yield [kWh/kWp/year]
Degradation	Yearly degradation rate of PV panels [%]
$WACC_{nom}$	Nominal weighted average cost of capital [%][13]
$WACC_{real}$	Real weighted average cost of capital [%][14]

The value for the WAAC nominal is set to 0.04 (the average between 3.8% and 4.1% = 3.95%), whereas the WAAC real is set to 0.02 (the average between 1.8% and 2.1% = 1.95%). Additionally, operation and maintenance (O&M) costs per year per kWp as a percentage of total capital expenditures was set to 2.5% (Fraunhofer ISE, 2018). Figure 20 shows the model structure for the conceptualization of the LCOE.

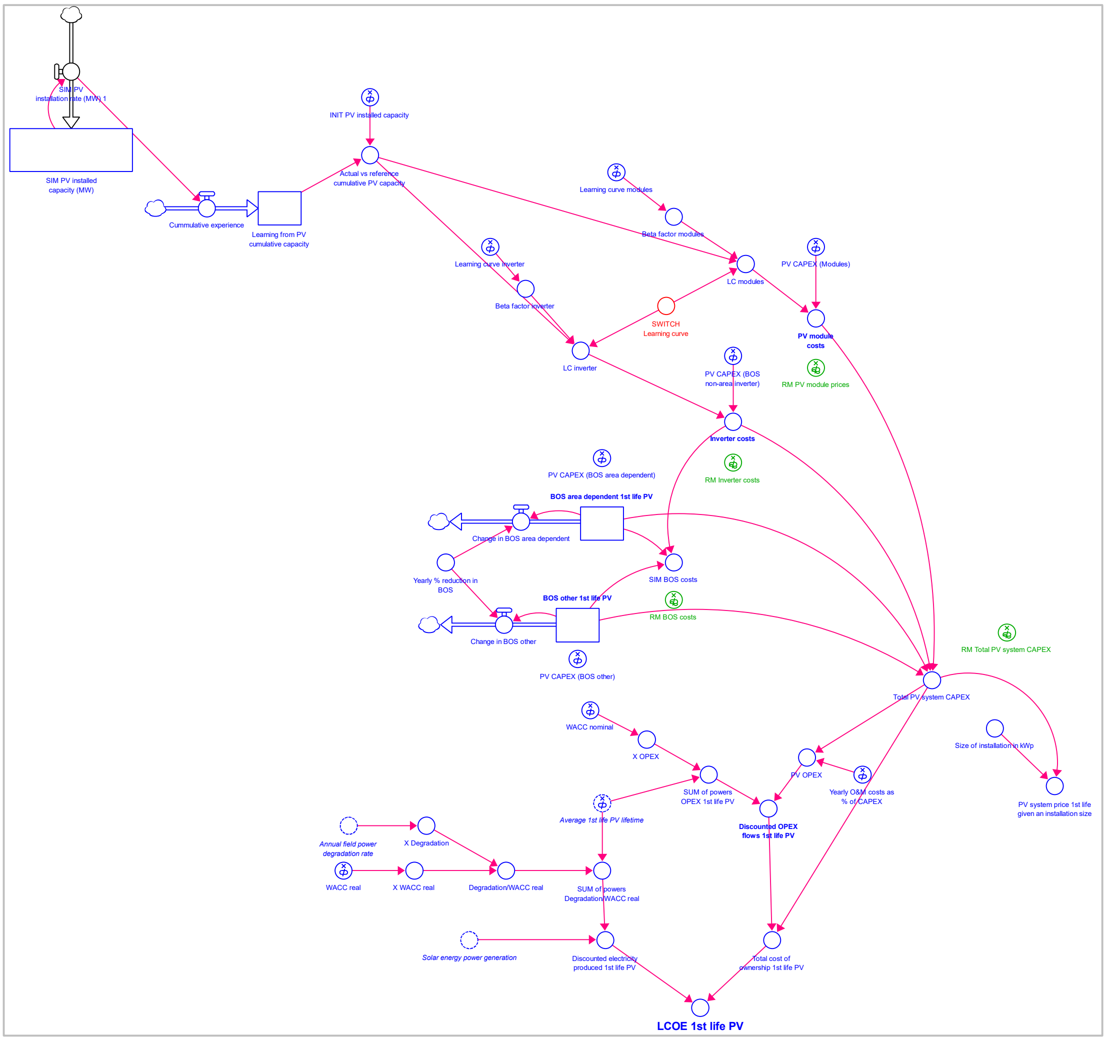


Figure 20 Model structure for the calculation of the LCOE for new PV

[13] Nominal weighted average cost of capital, taking into account inflation
[14] Real weighted average cost of capital, not taking into account inflation

For calculating the LCOE of second-life PV installations, the following assumption is made:

$$LCOE^{u} = LCOE^{n} \qquad \textbf{Eq. 20}$$

Where:

u	Scenario with 2nd life PV panels
n	Scenario with new PV panels

This means that for a 2nd life PV system to be financially attractive, its LCOE has to be lower, or at least the same, as the LCOE of a system with new panels (Rajagopalan et al., 2021). More especifically:

$$\frac{Price_{uPV} + Price_{BOSNonArea} + \left(\frac{1}{a} * Price_{nBOSArea}\right) + OPEX\sum_{t=1}^{N} \frac{1}{1+WACC_{nom}}^{t}}{\sum_{t=1}^{N} Yield * \frac{(1-Degradation)^{t}}{(1+WACC_{real})^{t}}} = \frac{Price_{nPV} + Price_{BOSNonArea} + Price_{nBOSArea} + OPEX\sum_{t=1}^{N} \frac{1}{1+WACC_{nom}}^{t}}{\sum_{t=1}^{N} Yield * \frac{(1-Degradation)^{t}}{(1+WACC_{real})^{t}}} \qquad \textbf{Eq. 21}$$

Where:

$BOS_{NonArea}$	Area-independent BOS
$BOS_{BOSArea}$	Area-dependent BOS

In the calculation of the financials for used PV, two aspects are of critical importance: (i) remaining lifetime, (ii) remaining power capacity.

Remaining lifetime

The equation below approximates the remaining lifetime of a PV module by subtracting the current year of the simulation from the PV lifetime value calculated by the model (as described in the policy scenario section in this document). The MAX built-in function in Stella Architect ensures the variable returns no negative value after performing the described subtraction (i.e., it chooses the maximum between the resulting number and zero).

Remaining PV lifetime=MAX(Used_1st_PV_lifetime-YearsHorizon, 0) **Eq. 22**

The "Average remaining lifetime 2nd life PV" is the value used for the financial calculation of the LCOE for used PV (see Eq. 23). As the formulation shows, the calculated value is equal to the mean of the arrayed values for remaining lifetime, taking only those values lying within a pre-defined boundary: the minimum and maximum year to calculate supply for reuse.

Average remaining lifetime 2^{nd} life PV= MEAN(Remaining_lifetime[Min_yr_to_calculate_supply_for_reuse:Max_yr_to_calculate_supply_for_reuse]) **Eq. 23**

The variables “Min yr to calculate supply for reuse” and “max yr to calculate supply for reuse” are introduced to reflect the fact that not all PV panels (i.e., only a percentage of the total decommissioned panels) will qualify to be deployed for reuse.

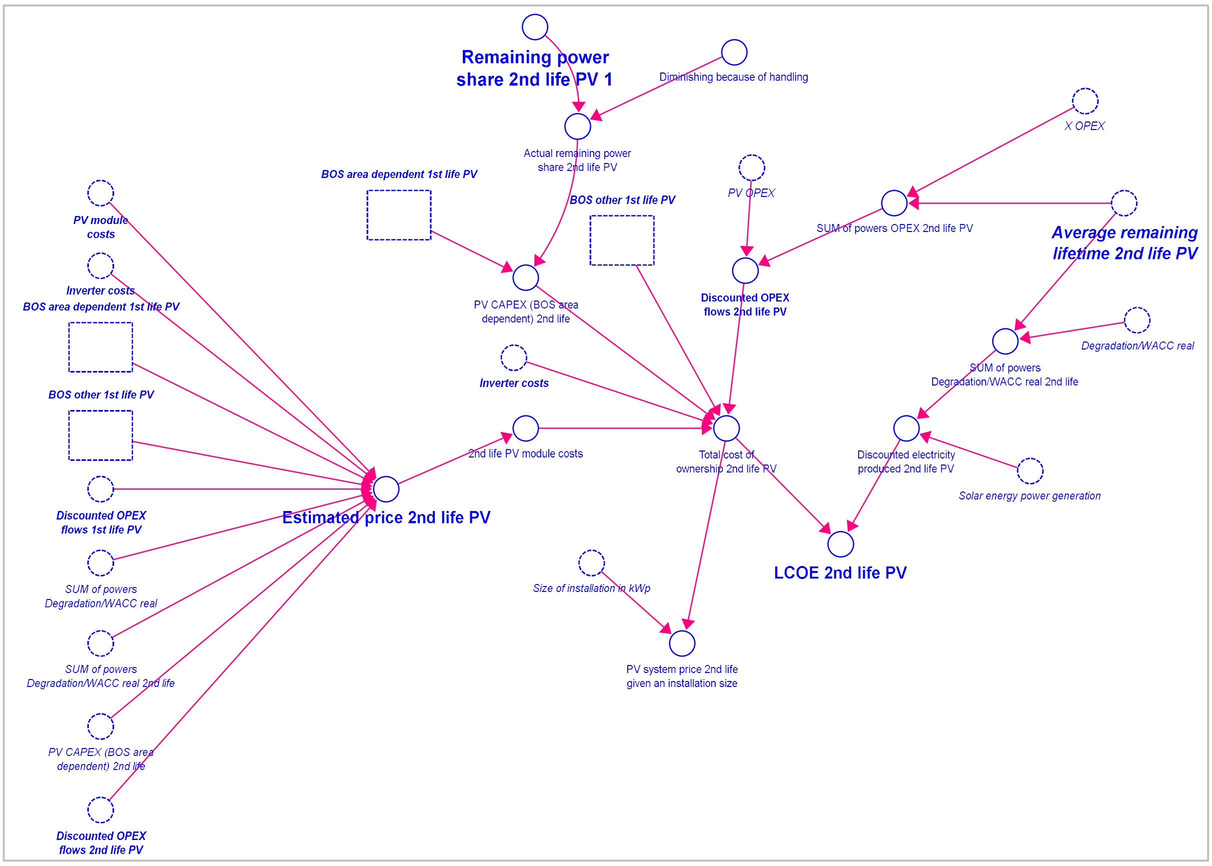


Figure 21 Model structure for the calculation of the LCOE for 2nd life PV

This phenomenon has been well-documented and researched in CIRCUSOL, where VITO together with FUTECH reported for instance, that the ¨financial viability of used PV strongly depends on its remaining power and lifetime Likely candidates include healthy modules (probably up to 10 to 15 years old), and modules with diode failure detected in their early years¨ (see Figure 22).

Costs of re-use: Extra costs compared to recycle/disposal

Avg. costs (EUR per module)	Healthy modules	Modules with diode failure	Modules with junction box failure
Dismantling	Same as dispose/recycling. May need more careful handling.		
Visual inspection; handling ("process fee" – SecondSol)	~20 EUR per batch → negligible for single module if batch large enough		
Cleaning	2		
Repair	0	5-10	40
Testing	?	?	?
Transportation (per 100km)	0.1 (used modules can be 30% higher due to lower packing density)		
Total *extra* costs (per module)	2+ Testing & extra transport	~10 + testing & extra transport	~40 + testing & extra transport
Total *extra* costs (per kWp) (if 250Wp/module)	**10+Testing & extra transport**	**40 + testing & extra transport**	**160 + testing & extra transport**

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Figure 22 Costs of re-use. Source: Presentation ¨CIRCUSOL Concept Review and Demo Definition¨, subsection ¨Second-life PV business case analysis¨ (VITO/FUTECH).

PV CAPEX for 2nd life

To calculate the price of 2nd life PV modules, we use the following formula:

$$P^u = a * P^n \quad \text{Eq. 24}$$

Where:

P^u	Price of used modules
P^n	Price of new modules
a	Remaining power share of used modules compared to new

In the model, this is translated to:

PV CAPEX (BOS are dependent) 2nd life = BOS_area_dependent_1st_life_PV/Actual_remaining_power_share_2nd_life_PV **Eq. 25**

Applying this same rationale to Eq. 21, and clearing it for calculating the estimated price for 2nd life PV:

$$(Price_{PV}^{u})$$

$$\neq \frac{Price_{PV}^{n} + Price_{BOS_{NonArea}} + Price_{BOS_{Area}}^{n} + OPEX \sum_{t=1}^{N} \frac{1}{1+WACC_{nom}}^{t}}{\sum_{t=1}^{N} \frac{(1-Degradation)^{t}}{(1+WACC_{real})^{t}}} \sum_{t=1}^{N} \frac{(1-Degradation)^{t}}{(1+WACC_{real})^{t}}$$
$$- Price_{BOS_{NonArea}} - \left(\frac{1}{a} \times Price_{BOS_{Area}}^{n}\right) - OPEX \sum_{t=1}^{N} \frac{1}{1+WACC_{nom}}^{t}$$

Eq. 26

$$Price_{PV}^{u} = Price_{PV}^{n} + Price_{BOS_{Area}}^{n} - \left(\frac{1}{a} \times Price_{BOS_{Area}}^{n}\right)$$

Eq. 27

In the model equation for "Estimated price 2nd life PV" (see Figure 21), the equation above is reflected as follows:

Estimated price 2nd life PV= ((PV_module_costs+Inverter_costs+BOS_area_dependent_1st_life_PV+BOS_other_1st_life_PV+Discounted_OPEX_flows_1st_life_PV)/"SUM_of_powers_Degradation/WACC_real")"SUM_of_powers_Degradation/WACC_real_2nd_life"-Inverter_costs-"PV_CAPEX_(BOS_area_dependent)_2nd_life"-Discounted_OPEX_flows_2nd_life_PV*

Eq. 28

Finally, Table 10 provides an overview of how the LCOE variables differ for new and used PV.

Table 10 Parameter values for the calculation of LCOE for new and used PV

Parameter value	Definition	New PV	2nd life PV	Units	Source
CAPEX PV panels	PV panel	The price decreases according to a designated learning rate	Depends on volume	EUR/kWp	Author's assumptions
CAPEX area independent	Inverter	The price decreases according to a designated learning rate	Same as new	EUR/kWp	Rajagopalan et al. (2021)
CAPEX area dependent	Cables and mounting structures	The price decreases according to an endogenously calculated percentage	Higher for 2nd life because after some years, they exhibit lower power density	EUR/kWp	Rajagopalan et al. (2021)

			than new modules. Therefore, a larger area is required to reach the same system capacity. The decrease in power output is also calculated by the model (i.e., "remaining capacity")		
Annual OPEX	Operation and maintenance cost per year per kWp as a percentage of total capital expenditures	2.5%	Same as new	EUR/kWp	Rajagopalan et al. (2021)
Module peak power	Expected nominal power production under ideal sunlight and temperature	Calculated endogenously to reflect increasing module peak power throughout time	Will depend on the age of the module. Calculated endogenously by the model	Wp	Authors' assumptions
Remaining lifetime	For 2nd life PV, this refers to the number of years until EOL	No aging	Calculated endogenously by the model depending on the year of failure	year	Authors' assumptions
Yearly degradation rate	The reduction in solar panel output over time that can be caused by climate,	0.8%	Same as new	Dimensionless	See section 9.1.1.5

	module type, racking system, among others				

9.4. ENVIRONMENTAL SUBSECTOR

9.4.1. PV WASTE

The model structure for PV reuse and recycling will be shown in the policy formulation section of this report.

9.4.2. CO2 EMISSIONS

The main explanation for CO2 emissions in the model is given by the emissions per kilowatt-hour (kWh) of solar power. Although solar panels do not produce emissions while producing electricity, they do produce emissions during their lifecycle. Raw material extraction and transport of materials used in solar panel production and the manufacturing process represent the most significant sources of GHG emissions for PV panels. Over time, however, solar panel production has improved, with increased module efficiency and reduced costs and emissions. According to Louwen et al. (2016), greenhouse gas emissions from PV production show a downward trend with increasing installed capacity, with learning rates (LR) of 16.5±2.31% and 23.6±1.86% for poly- and monocrystalline based systems respectively. Because monocrystalline panels are the most common, the model takes a 16.5% LR.

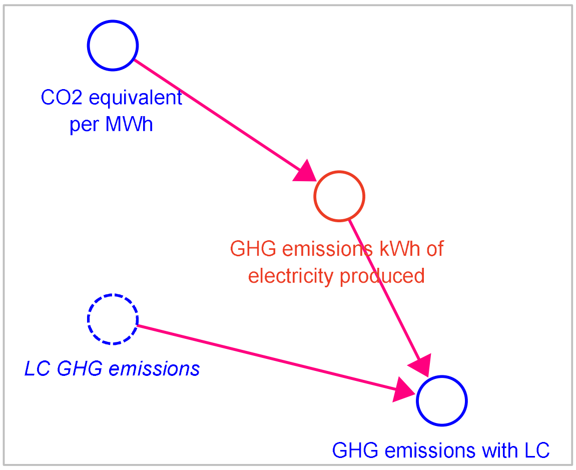

Figure 23 Model structure for the calculation of GHG emissions

Table 11 Assumptions for the conceptualization of the environmental impact of PV

Variable name	Definition	Value	Units	Source
Average GHG emissions of solar PV	Life cycle greenhouse gas emissions of a PV rooftop system operated in Germany	50	CO2-eq/kWh	Fraunhofer ISE (2020)
Learning rate for GHG emissions	Reduction in GHG emissions each time the cumulative manufacturing quantity doubles	16.5%	Dimensionless	Louwen et al. (2016)

The inclusion of the learning rate for GHG emissions responds to the evidence showing that with increasing PV installed capacity, GHG emissions show a downward trend (Louwen et al., 2016). In the previously cited report, researchers observe a stronger learning rate for mono- compared to polycrystalline silicon-based PV systems (LRs of 16.5±2.31% and 23.6±1.86% for poly- and monocrystalline based systems respectively).

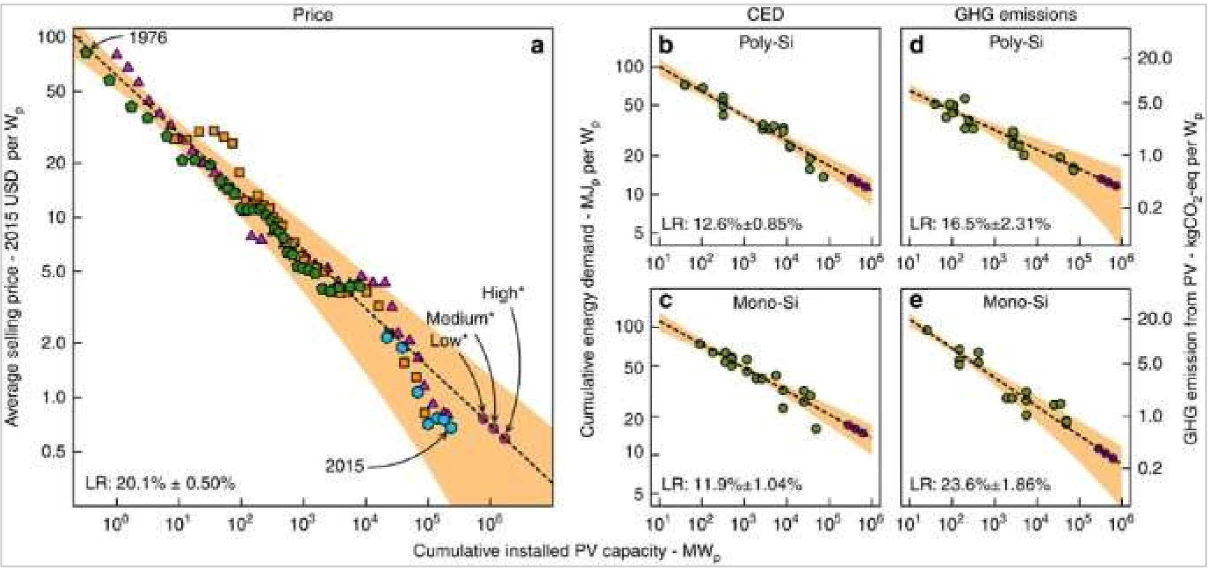

Figure 24 Experience curves for cumulative energy demand and GHG emissions from production of mono- and polycrystalline silicon-based PV systems. Source: Louwen et al. (2016)

10. CONCLUSIONS

In addition to motivations such as a personal contribution to the energy system transformation, Installations of new PV systems in Germany are largely driven by financial factors such as FITs and the related economic profitability. Rising electricity prices are the main driver for the market uptake of new PV (also of battery systems for self-consumption). However, as evidenced by model results, even with constant electricity prices and the abolishment of government incentives, PV self-consumption is likely to gain significant market share in the future due to decreasing equipment prices.

The structure of the simulation also evidenced the extent to which the volume of available 2nd life PV is highly dependent on several factors that bear a high degree of uncertainty. These include, among others, growth rates of PV installed capacity, curves of failure rates, age cohorts selected for reuse, repair types of used PV, as well as collection and recovery rates. In particular, the volume available for "preparation for reuse" is strongly defined by the age cohort composition of the decommissioned PV and the trajectory of the installation rate in a specific location. There are, therefore, limits to the maximum amount of collected and processed PV for reuse. As evidenced by model results, recycling volumes are, in fact, still much more significant and surpass by far the volumes collected, in the best-case scenario, for reuse. This constitutes an important remark for projects like CIRCUSOL, which concentrates on the potential for PV reuse. The described results also suggest that legislative and financial support should still be given for the advancement of recycling technologies. It is currently well-known that recycling PV waste is challenging not only as a result of the high operational costs caused by the limited number of PV panels reaching their EoL, but also by the lack of well-established recycling technologies (Franco & Groesser, 2021). Finally, model results showed that the effect of switching from a regular loss scenario to an early loss scenario (when modeling failure rates for new PV) is significant. As time progresses, more data on PV failure will be available to better estimate failure curves and therefore, volumes of PV available for reuse.

Financially speaking, LCOE results show 2nd life PV is not economically attractive when compared to new PV. In some cases, however, the willingness to pay could be high for 2nd life PV even when it is not profitable. Examples include customers driven by environmental concerns, such as in the case of the cohousing projects, or very specific market segments (e.g., hospitals, schools) for whom the influence of aesthetics and space requirements is not that strong. Other CIRCUSOL deliverables have provided empirical evidence for this.

Policy testing scenarios (published in Deliverable D1.4) showed PV panels exhibit a durability-recyclability trade-off in multiple design dimensions. Additionally, a stricter recycling target does not necessarily translate to a more recyclable product. On the contrary, high recycling quotas indirectly encourage PV manufacturers to influence durability strategies by shortening product lifetime. One suggested recommendation could be not using uniform legislative targets regarding recycling and collection rates for all product categories, but rather adapting these targets to product and market characteristics, as well as environmental impact priorities. In regard to reuse, it is important to highlight also that there are other challenges not tested in this simulation model. For instance, modules of different power, efficiency, voltage, or current cannot be directly connected in series or parallel into a solar system due to mismatch losses. This means that the recyclers would have to have hundreds of large containers, each for a particular type of module with a particular efficiency. They would have to accumulate a large enough number of the same modules with the same efficiency in order to make a sale, unless they deal exclusively with waste modules from large solar farms. This would significantly increase the cost for the reused modules and affect their market uptake

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[i] The EEG was established in 2000 and then amended both in 2004 and 2009.

[ii] Wind and solar are the main RES, followed by biomass and hydropower.