

# Swiss PV Circle

## Work package 3 - Forecasting

### Forecasting and visualisation of the end-of-life volume of PV systems (2000-2050) including characteristics and age analysis

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## Executive Summary

The rapid expansion of photovoltaics (PV) as part of the energy transition is expected to lead to a significant increase in used modules. To manage the growing waste streams and promote resource efficiency, the circular economy is an economic model that aims to create circular material flows. Although 50% of PV modules are technically reusable after their first life cycle, little is known about the age of end-of-life (EoL) modules and the factors that lead to system decommissioning or replacement, which hinders circular activities. Therefore, as part of the Swiss PV Circle project, analytical approaches and data from various sources were used within work package 3 to improve the prediction of cycling activities. As the data basis for effective EoL quantities from previous years is still very limited, the collection quantities from SENS eRecycling from previous years were initially used to gain an insight into the future development of waste quantities. In a second step, this figure was compared with results from existing scientific studies in order to better understand current assumptions for calculating forecasts.

Furthermore, more than 500 EoL assets were analysed for various parameters using qualitative analysis to gain a better understanding of the characteristics of current return volumes to improve reuse practices. Finally, these EoL assets were used as the basis for a scientific study to gain insights into the age and machine learning (ML)-based classification of EoL assets. In a third step, the ML model was applied to identify further EoL assets in the existing dataset to further concretise the forecasting.

This report is structured as follows: Firstly, the initial situation is described, followed by the methods used to collect and analyse the data. The results from the various approaches are then presented and compared with existing studies. Finally, the results are discussed and the most important findings are summarised again, followed by a concluding conclusion and an outlook for the future.

## 1. Introduction

Forecasting refers to the systematic prediction of future developments or events on the basis of historical data, current trends and relevant influencing factors.<sup>1</sup> In the context of EoL flows, forecasting refers to the prediction of the quantity, composition and temporal occurrence of products that have reached the end of their life cycle and are ready for reuse, recycling or disposal. Various methods are used, e.g. statistical models, time series-based methods, machine learning approaches or scenario-based projections, with the aim of enabling well-founded decisions for waste management, the circular economy and resource planning.

The decisive factor in enabling forecasting is the data available for this purpose. The following basic requirements apply:<sup>2</sup>

- **Historical data:** Past developments are often a basis for forecasts. This data must be sufficiently long, reliable and precise.
- **Data quality:** Missing values, outliers and inconsistencies should be recognised and corrected if necessary.
- **Relevance of the data:** The data used must be representative of the phenomenon to be predicted.

Furthermore, the relevant influencing factors that determine the forecast event should be identified. These include, for example, technological developments, legal framework conditions and market trends. The choice of a suitable forecasting model is also crucial, depending on the type of data and the objective of the forecast. Another important criterion is stability and the recognition of patterns in the historical data. Forecasts are particularly reliable when recurring trends or seasonal effects are recognisable; however, the accuracy of forecasts is limited in the case of highly volatile processes. As every forecast contains uncertainties, these should be quantified and communicated - for example through confidence intervals or scenario analyses. Scenario-based forecasts are particularly useful when several uncertain influencing factors play a role. Finally, continuous validation of the forecasts is necessary in order to recognise deviations and adjust the model if necessary. Changes in the environment, such as technological innovations, should be regularly incorporated into future forecasts.<sup>3</sup>

These basic requirements show that forecasting is primarily dependent on the quality of the data and the information available. In reality, however, data sources are often fragmented, inconsistent and require a great deal of effort for quality assurance. For this reason, several steps and sub-processes are necessary to enable forecasting.

The first studies for forecasting PV waste volumes have already been carried out in the past<sup>4</sup>, but these studies are outdated and rely on key figures from a limited geographical context to develop the results. Other studies (e.g.<sup>5</sup>) are based on generalised basic assumptions that need to be understood and questioned. These studies will be discussed in more detail later in this report.

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<sup>1</sup> Makridakis, Wheelwright, and Hyndman, "Forecasting."

<sup>2</sup> Makridakis, Wheelwright, and Hyndman; Goodwin et al, "Principles of Forecasting."

<sup>3</sup> Hyndman and Athanasopoulos, *Forecasting*.

<sup>4</sup> Forti, Baldé, and Kuehr, "E-Waste Statistics"; Rabaia, Semeraro, and Olabi, "Recent Progress towards Photovoltaics' Circular Economy"; Magalani et al, "Study on Collection Rates of Waste Electrical and Electronic Equipment"; Weckend, Wade, and Heath, "End of Life Management."

<sup>5</sup> Czajkowski et al, "Prediction of the Market of End-of-Life Photovoltaic Panels in the Context of Common EU Management System."

## 2. Methods used

The data collection and analysis methods used in the project are presented below. Firstly, collection data from SENS eRecycling from recent years was used to create an initial estimate for the forecast of future waste volumes using polynomial regression. Secondly, this data was compared with results from scientific studies in order to validate the calculation assumptions. Thirdly, an exploratory qualitative analysis of over 500 EoL plants was carried out, in which various parameters were analysed in order to gain a better understanding of the characteristics of the return volumes. A fourth element of the study was the application of statistical models (Kaplan-Meier analysis and logistic regression model), which made it possible to determine the age of the plants and classify EoL plants. In the future, the approach is to be extended to ML-based identification of further EoL plants in the data set in order to make the forecasting models more precise.

### 2.1 Data collection

The data used for this study came from four main sources. Firstly, we used a public dataset from the Opendata.Swiss portal, which is regularly published by the Swiss Federal Office of Energy (SFOE). The dataset contains the electricity production plants registered in the Swiss Guarantee of Origin system with location, installation date, installed capacity and PV plant type. By the end of 2023, this dataset included around 225,000 PV systems between 0 and 35 years old.<sup>6</sup>

The second, non-public data source, provided by the SFOE as part of the Swiss PV Circle project, comprises 15 time-series datasets recording the monthly energy production of each PV system between 2009 and 2023. Another non-public source, provided by the Swiss take-back system SENS eRecycling and partner of the Swiss PV Circle project, includes all collection orders from 2017 to June 2024 requested by companies or collection centres for the collection and recycling of EoL PVs<sup>7</sup>. The dataset contains the collection address, date, quantity (kg), PV panel type, module condition and EoL reason of each collection order. In addition to the collection orders, the aggregated collection quantities for the years 2015 - 2023 were also provided. For example, the total quantity of EoL PV modules collected in 2023 was 1,000 tonnes (t).

As a fourth data source, we included a dataset from the SPF Institute for Solar Technology containing records of hail damage to PV installations in Switzerland in 2021, which helped to identify additional disused PV installations. In addition to these four primary data sources, we utilised historical imagery from Google Earth Pro to verify EoL occurrences and support the development of a comprehensive dataset.

### 2.2 Data preparation

To create a comprehensive database for legacy PV installations, we started by merging data sources, mainly using addresses or product identifiers, to link and reference unique PV installations in the datasets. This process required extensive data cleansing and preparation to remove records with gaps caused by inconsistent data tracking in the sources used, resulting in an inevitable loss of incomplete data points. Merging these sources also allowed us to identify additional EoL-PV assets and supplement the existing data through an iterative cross-referencing process to improve credibility and completeness<sup>8</sup>. In this way, we were able to identify 522 EoL PV systems and a total of approximately 157,000 PV systems that contained all

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<sup>6</sup> Opendata.Swiss, "Electricity Production Plants - Opendata.Swiss."

<sup>7</sup> SENS eRecycling, "Recycling system for photovoltaics in Switzerland."

<sup>8</sup> Patton, "Enhancing the Quality and Credibility of Qualitative Analysis."

relevant information for further data analysis. However, the data set used for EoL PV systems only represents a sample and not the totality of all existing PV systems with EoL occurrences.

## 2.3 Data analysis

Due to the considerable limitations in the available data, especially with regard to EoL plants and quantities, several steps are necessary to enable forecasting. The data analysis techniques that have been used so far in WP3 to enable improved statements about EoL plants are described below. As mentioned above, retrospective considerations continue to be an important basic building block to enable a view into the future, which is why some analyses do not include classic forecasting, but serve to describe the current actual state.

### 2.3.1 Qualitative analysis

As an additional step, we used an explorative qualitative approach to analyse the characteristics of PV systems that have reached the end of their operating life<sup>9</sup>. This analysis includes, among other things, the investigation of the reason for decommissioning, the year of installation, the installed capacity (kWp) and the geographical distribution of EoL and active systems. As the results of this qualitative analysis are to be the subject of a further scientific study, the results are presented in aggregated form.

### 2.3.2 Quantitative analysis

#### *Kaplan-Meier survival analysis*

Next, a Kaplan-Meier survival curve was applied, which is a non-parametric statistical method for estimating survival probabilities over time by examining different time intervals<sup>10</sup>. The Kaplan-Meier estimator, also known as "product frontier estimator", calculates survival probabilities by determining the probability of an event occurring at each specific point in time. Although the Kaplan-Meier estimator is primarily used in medical research, it has been used in reliability studies to estimate product survival probabilities<sup>11</sup>. Due to its adaptability, this method is therefore well suited for our study, as it provides robust estimates of survival times for EoL-PV systems while taking censored data into account<sup>12</sup>. Censored data refers to observations where the event of interest (e.g. EoL) did not occur during the observation period, assuming that these systems remain "at risk" for the event<sup>13</sup>. This assumption fits our study as it takes into account "at risk" PV systems where an EoL event could not be definitively attributed due to a lack of available information on the totality of EoL events. The survival probability  $S(t)$  at a given time ( $t$ ) is estimated by:

$$\hat{S}(t) = \prod_{i:t_i \leq t} \left(1 - \frac{d_i}{n_i}\right)$$

where  $d_i$  is the number of events (e.g. system failures) that occur at time  $t_i$  and  $n_i$  is the number of "at-risk" systems immediately before  $t_i$ . For each time interval, the survival probabilities are derived by dividing the number of operational PV systems by the total number of "at risk" systems. The cumulative survival probability

<sup>9</sup> Thomas, "A General Inductive Approach for Qualitative Data Analysis."

<sup>10</sup> Altman, *Practical Statistics for Medical Research*.

<sup>11</sup> Widodo and Yang, "Application of Relevance Vector Machine and Survival Probability to Machine Degradation Assessment"; Ragab et al, "Remaining Useful Life Prediction Using Prognostic Methodology Based on Logical Analysis of Data and Kaplan-Meier Estimation".

<sup>12</sup> Goel, Khanna, and Kishore, "Understanding Survival Analysis."

<sup>13</sup> Prinja, Gupta, and Verma, "Censoring in Clinical Trials."

over a given time period is then calculated by applying the multiplication law, combining the survival probabilities from all previous intervals.

### *Polynomial regression*

For an initial assessment of possible EoL volumes in the coming years, polynomial regression was used to describe non-linear relationships between one or more variables. Polynomial regression enables a more differentiated and precise modelling of complex trends and is therefore suitable for calculating the EoL quantities that will develop over time. The relationship between the independent variable  $x$  and the dependent variable  $y$  results from:

$$y = b_0 + b_1x + b_2x^2 + \dots + b_nx^n + e \text{ where}$$

$b$  = coefficients

$e$  = Error term

The collection volumes of SENS eRecycling from previous years since 2015 were used as the basis for this initial estimate. It is important to note that these figures do not represent the entirety of all EoL volumes, as a significant proportion is exported abroad through uncontrolled exports. There are currently no exact estimates of the proportion of export volumes of Second Life modules to mainly non-European countries. Another problem is that these quantities are not tracked by customs under a separate export number. However, initial studies suggest an export share of between 30 and 70% to countries such as France, Germany and Italy.<sup>14</sup>

### *Logistic regression*

In the final stage of data analysis, a logistic regression (LR) model was used to classify the legacy assets in the dataset. LR is a widely used classification model that is particularly effective for binary and linear classification problems with linearly separable classes<sup>15</sup>. LR was favoured in this study due to its interpretability, computational efficiency and ability to provide probability-based predictions that allow us to assess the likelihood of EoL occurring at a PV plant. Alternative models such as decision trees or support vector machines could also perform binary classification, but are often less interpretable or require more computational resources<sup>16</sup>. Given the goal of understanding the key characteristics that influence EoL, LR was considered the most appropriate choice for classifying whether a PV plant is at the end of its life cycle ("1") or still active ("0"). The probability that for the given values of the independent variables the dependent variable  $y$ , i.e. whether the PV system is at the end of life, is "1" or "0" is given by:

$$p(y = 1) = \frac{1}{1 + e^{-(b_1x_1 + \dots + b_kx_k + a)}} \text{ and } p(y = 0) = 1 - \frac{1}{1 + e^{-(b_1x_1 + \dots + b_kx_k + a)}}$$

where  $x_{1-k}$  represent independent variables corresponding to the characteristics associated with each PV system. In addition, the regression coefficients  $b_{1-k}$  quantify the effect of each predictor on the probability that the dependent variable is "1" and indicate the influence of each feature on the EoL classification.

<sup>14</sup> Hansen et al, "The Dark Side of the Sun: Solar e-Waste and Environmental Upgrading In."

<sup>15</sup> Subasi, *Practical Machine Learning for Data Analysis Using Python*.

<sup>16</sup> Stoltzfus, "Logistic Regression."

### 3. Results

The results obtained in WP3 are presented below and then discussed. As both 0 and 0 were prepared as part of a scientific study, the results in this report are only aggregated and summarised without illustrations.

#### 3.1 Characteristic values of EoL systems

In order to be able to make improved statements about the characteristics of dismantled PV systems, these were analysed using a qualitative-explorative approach. The basis for this investigation was around 530 systems, which were identified as clear EoL systems through the data preparation process and the merging of various sources, and which also contained all the necessary information. The basis for the assignment of the EoL reason was provided by the collection orders from SENS eRecycling, in which a collection reason (e.g. 'end of use', 'material defect' or 'other') was stored. In recent years, systems were particularly frequently given the reason 'hail damage' or 'storm damage'. In order to supplement and verify the information, the age of the turbine and the satellite photo were checked for the assignment of the EoL reason in order to prove whether a change (e.g. repowering) or a final dismantling (e.g. end of use) had taken place. The review of the satellite history also revealed that a large proportion of the turbines were dismantled due to construction work. As already mentioned at 2.1, a data set on hail damage from 2021 was used for the analysis via the SPF Institute for Solar Technology at the OST University of Applied Sciences. However, as this data set could distort the picture of a possible distribution of the EoL reasons, the presentation of the EoL reasons without the SPF hail data is shown at Figure . The figure shows that only one sixth of all installations were given the reason 'end of use'. A much larger proportion of EoL facilities entered the waste stream due to unforeseen events such as damage, material defects or hail. It is also interesting to note that the largest proportion of identified EoL plants have been repowered. However, it is not possible to say for certain whether this repowering was caused by a material defect or for purely economic reasons.

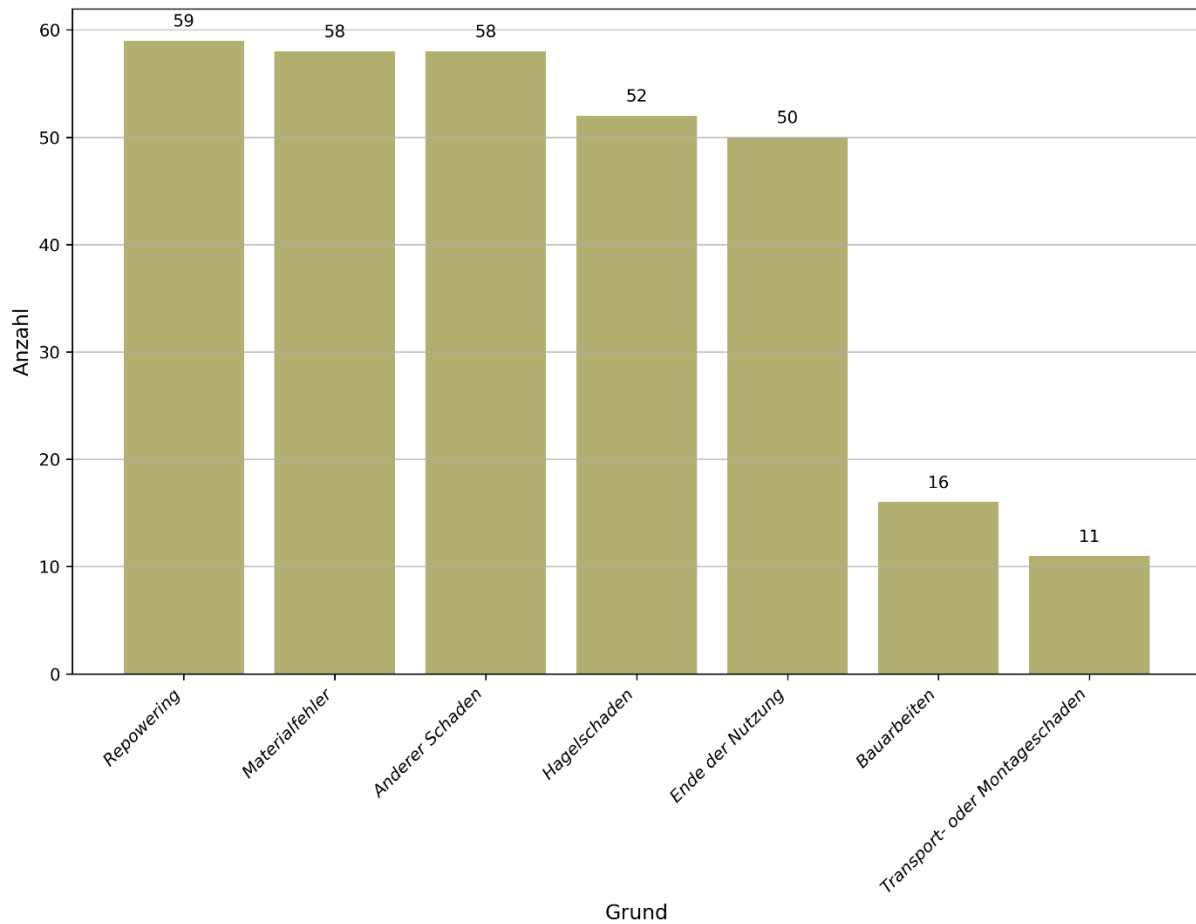


Figure 1: Identified EoL reasons for dismantled systems.

The year of installation of dismantled systems was also analysed, which showed that most of the systems were installed after 2009 and a significant proportion were only installed from 2015 onwards. The reason for this observation could be, on the one hand, the increasing rise in PV systems, which at the same time brings with it an increasing rise in EoL systems. Furthermore, the increasing number of extreme weather events could have a growing impact on the more built-up PV area. Investment decisions for systems installed in the last 7 - 10 years could also lead to premature repowering .<sup>17</sup>

<sup>17</sup> Sodhi et al, "Economic Lifetimes of Solar Panels."

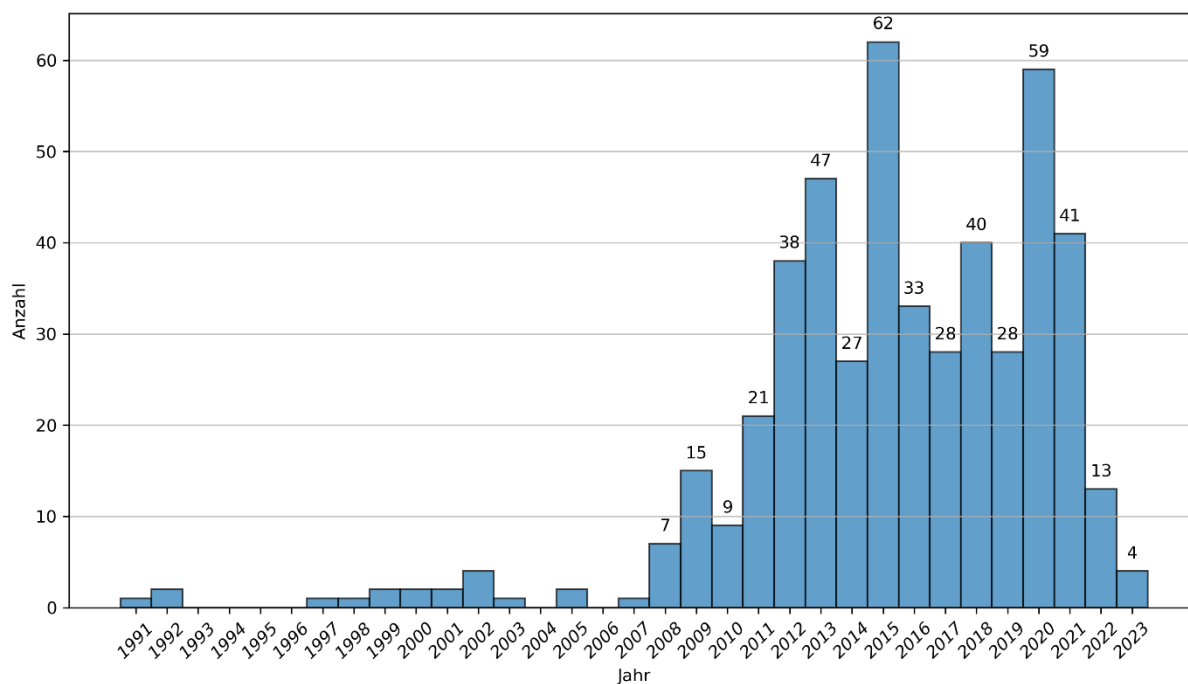


Figure 2: Years of installation of EoL systems.

Another interesting parameter for analysing the characteristics is the installed capacity of the systems. While EoL installations had a capacity of around 114kWp, the average capacity of all active installations is 24kWp. In addition, around 89% of all active installations have a capacity of less than 30kWp, compared to only around 48% of EoL installations. There may be several reasons for these different figures. On the one hand, it may be that owners of small systems tend to bring them to collection points (where they are ultimately no longer traceable in the data set) rather than ordering a collection. Furthermore, it could be that private owners are more likely to hand over their systems to intermediaries for direct resale (e.g. as second-hand modules) or sell them via online marketplaces. Nevertheless, it can also be surmised that financial incentives to change systems early, for example through repowering, are more relevant for larger systems on an industrial scale. This could also have an influence on the large capacity of EoL plants.

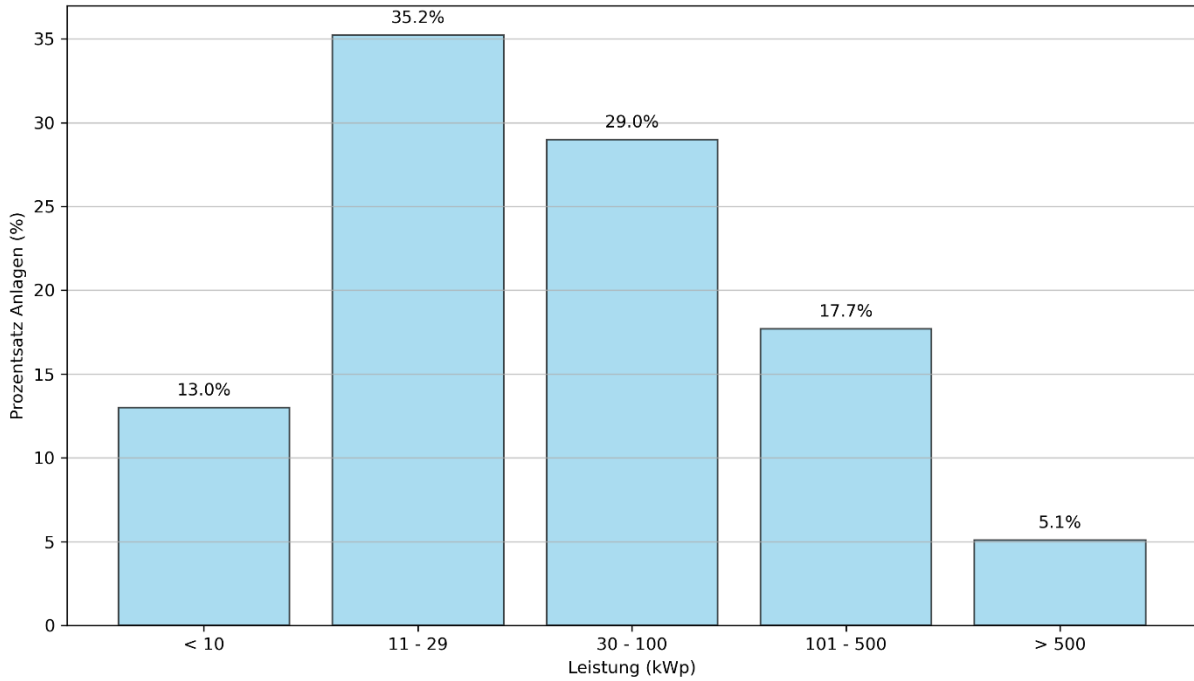


Figure 3: Distribution of installed capacity (kWp) by category for EoL systems.

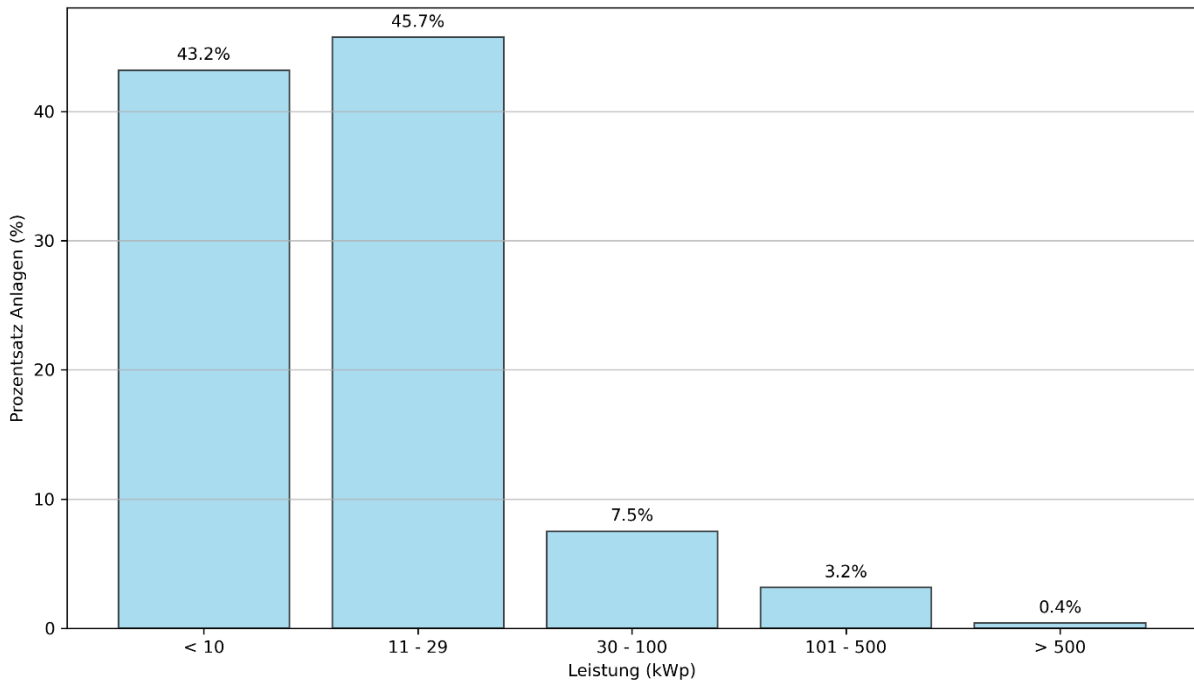


Figure 4: Distribution of installed capacity (kWp) by category of all currently installed PV systems.

Further analyses, such as the geographical classification of EoL plants, were also carried out as part of WP3. Overall, this analysis showed that dismantled plants have characteristic features that enable them to be separated from plants that are still active. In addition to the satellite photo, the energy production data can be an important indicator for identifying other EoL installations, for example in the event of changes in the yields generated. It was also found that systems with confirmed EoL have received an extension more frequently than active systems, which may indicate a change and subsequent increase in capacity for new modules. This information is an important prerequisite for finding out whether an algorithmic classification of EoL systems using an ML model is possible.

### 3.2 Age of EoL PV systems

As the age of the PV system is a decisive factor in assessing the reuse capability, a Kaplan-Meier analysis was used to analyse the service life of identified EoL systems. The analysis showed that the median survival time of the analysed EoL modules is approximately seven years (interpolated value). These results are in line with previous studies that identified economically motivated early replacement decisions (repowering) and early failure events (weather events, design errors, etc.) as key factors for premature EoL<sup>18</sup>. Interestingly, it was found that only a small proportion (~4%) of the dismantled systems were older than 15 years, while a significant proportion (20%) entered the EoL stream within the first year of life.

One particular factor for early failures was hail damage, which occurred regardless of the age of the modules. As increasingly extreme weather events are expected due to climate change, this could play a greater role in the future. Furthermore, the median lifetime of seven years has already been discussed in previous studies (e.g.<sup>19</sup>) as the economic lifetime of the system, which was confirmed by the high proportion of repowering systems (see 3.1). The Kaplan-Meier curve showed that PV systems still had a survival probability of around 94% after 30 years when analysing all systems installed to date (including EoL), which speaks in favour of the general longevity of the products. These results emphasise the need to take regulatory measures to promote the sustainable use of PV modules and to encourage the reuse of intact modules.

### 3.3 Forecasting EoL volumes until 2050

#### 3.3.1 Forecasting using SENS pick-up quantities

In order to prepare a forecast, the first step was to calculate potential future EoL volumes, taking into account the SENS collection volumes (see 2.3.1). This calculation forecasts an increase in the EoL volume to approx. 22,000 tonnes by 2050. The calculated values for the years 2024 - 2050 are attached in Table 1 in the Annex. This initial estimate is intended to show a possible first step towards visualising the EoL volumes, but it must be emphasised here that the collection volumes from SENS do not represent the absolute total volume of the EoL plants, since, as explained at the beginning, a considerable proportion flows into exports<sup>20</sup>. Taking into account the current export data for PV from the Federal Statistical Office, it can therefore be assumed that at least 30% (see Deliverable 5.2) of the currently reported collection data could flow into exports<sup>21</sup>, i.e. around 200 tonnes in 2023. In addition, direct commercial resales of second-life modules within Switzerland (e.g. as second-hand modules) can further influence the number of unreported cases. There are no official figures on this so far.

It can be seen that various factors can influence the calculation of EoL volumes in the coming years, but the current data basis only provides a few insights into potential deviations from the reported collection volumes. In order to provide further insights, an improved overview of the actual number of existing EoL facilities is necessary, which is why a more complex approach to identifying existing EoL facilities was developed below.

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<sup>18</sup> Gupta et al, "Impact of Hailstorm on the Performance of PV Module: A Review"; Sodhi et al, "Economic Lifetimes of Solar Panels."

<sup>19</sup> Sodhi et al, "Economic Lifetimes of Solar Panels."

<sup>20</sup> Hansen et al, "The Dark Side of the Sun: Solar e-Waste and Environmental Upgrading In."

<sup>21</sup> BAZG, "Federal Office for Customs and Border Security."

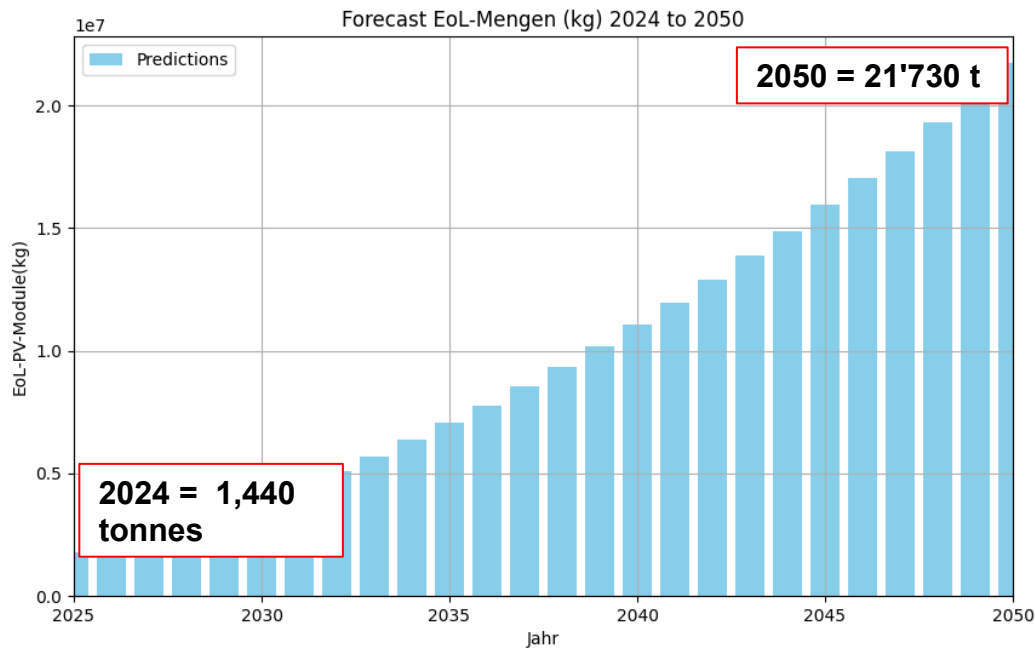


Figure 5: Initial estimate of future EoL volumes up to 2050, based on regression model. The collection volume depicted for 2024 was also calculated using the model, as no official figures for 2024 were available at the time of measurement.

### 3.3.2 Forecasting using EoL classification

#### Training and testing ML model

In order to enable a forecast based on the absolute quantity of identified EoL plants, several steps had to be taken. Firstly, a logistic regression model with around 1,200 data points was trained to analyse the classification of EoL plants and around 300 data points were tested (weighting 80% to 20%). For the application of the model, a data set was compiled that provides the greatest possible amount of information (e.g. age, location, capacity, yield) for each plant. The results of the logistic regression show that this model is able to classify EoL PV systems with a high degree of accuracy. The overall accuracy of the model was 89.3%, while a 10-fold cross-validation yielded an average accuracy of 85.4% with a standard deviation of 2.59%. These results indicate robust model performance, even with different data sets.

A look at the Confusion Matrix shows that the model has a higher specificity (93.7%) than sensitivity (86.3%). This means that the model is better at correctly recognising active systems as "not EoL", while it is slightly less accurate at correctly identifying systems as EoL.

The most important factors influencing the EoL risk were determined using the calculated odds ratios. This showed that geographical variables, such as the canton of Lucerne (LU), have a particularly high significance - the risk of an EoL occurrence was 21 times higher here than in other regions. Other important influencing factors were the age of the system, the number of months of interruption and the "KEV" subsidy programme for older systems. The model also indicates that systems with certain yield profiles (e.g. Yield\_2019 and Yield\_2016) are more susceptible to early EoL.

#### EoL classification

In a second step, the pre-trained model was used to identify further potential EoL plants in the complete data set (n= 157,000). For this purpose, a subset of the EoL dataset (n=100) was first created in order to reduce distortions in the sample (e.g. due to canton or year-specific hail

damage). In addition, a balanced ratio between EoL systems (10%) and active systems (90%) was aimed for, as it can be assumed that the overall proportion of uninstalled systems is comparatively low<sup>22</sup>. Interestingly, despite the adjusted data set, the model still showed that the cantonal variables for Lucerne and Zug still have the greatest influence on the EoL classification, which, in addition to the increased occurrence of hail, could also be related to the higher density of PV systems (10 systems/km<sup>2</sup>; in comparison, in Bern it is 6 systems/km<sup>2</sup>)<sup>23</sup>. Furthermore, the accuracy of the model increased to 93.7% with an adjusted sample.

To classify new EoL installations, the model calculated the probability of occurrence of an EoL event for each data point. Data points with a probability above 0.5 were classified as "EoL", resulting in a total number of 3,183 classified installations (see Figure 6). Using a conversion coefficient of 100kg/kWp, this results in a total of 23,061 tonnes classified as EoL by 2023 - corresponding to 2% of all the installations analysed.

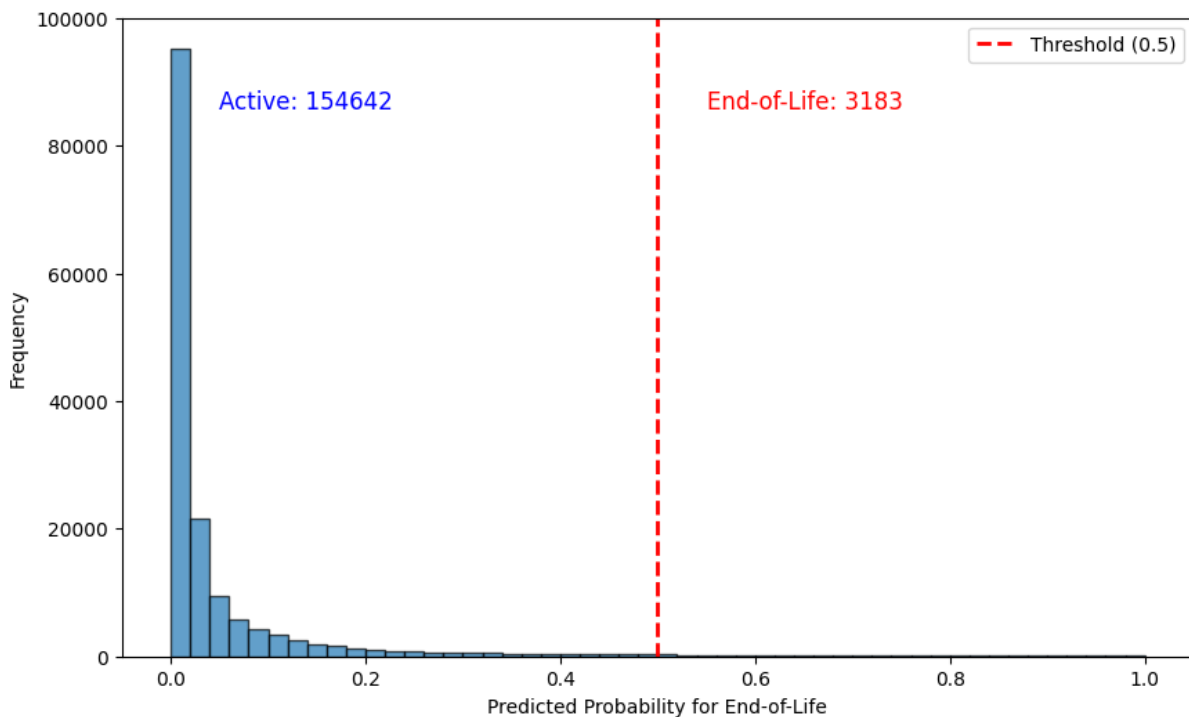


Figure 1 : Distribution of classified end-of-life plants.

In a third step, the classified EoL volumes served as the basis for a forecast calculation in which the increase in the curve was modelled on the basis of the SENS collection volumes from 2015 to 2023. A polynomial regression was again used for the forecast, which predicts an increase in EoL volumes to around 90,000 tonnes by 2050 (see Figure 7).

<sup>22</sup> Rabaia, Semeraro, and Olabi, "Recent Progress towards Photovoltaics' Circular Economy".

<sup>23</sup> Opendata.Swiss, "Electricity Production Plants - Opendata.Swiss."

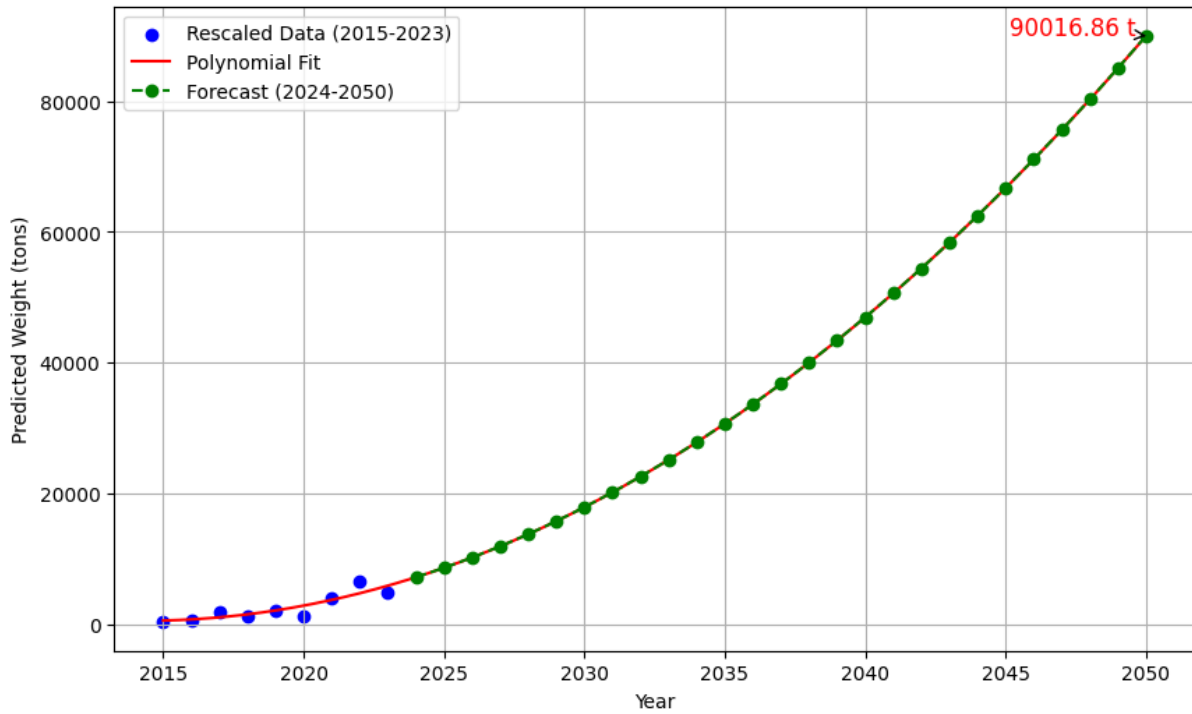


Figure 2 : Updated forecast up to 2050 taking into account ML-classified EoL volumes up to 2023.

### 3.3.3 Comparison with existing studies

To enable a comparison of this first calculation for Switzerland with existing studies, two studies were analysed as examples, which used different methods for calculating EoL quantities.

#### Forecast study IRENA and Wambach Consulting (2022)

The forecast is based on the report "End-of-Life-Management Solar Photovoltaic Panels" published by the International Energy Agency (IEA) together with the International Renewable Energy Agency (IRENA) in 2016<sup>24</sup>. The Weibull distribution is used as the methodological basis for calculating the EoL quantities, assuming an average PV system service life of around 30 years and a loss probability of 99.9% after 40 years at the latest. The Weibull curve is calculated under:

$$F(t) = 1 - e^{-\left(\frac{t}{T}\right)^\alpha}$$

t = time in years

T = Average lifetime

α = shape factor, responsible for the S-shape of the Weibull curve

<sup>24</sup> Weckend, Wade, and Heath, "End of Life Management."

<sup>25</sup> "Swissolar," 2025.

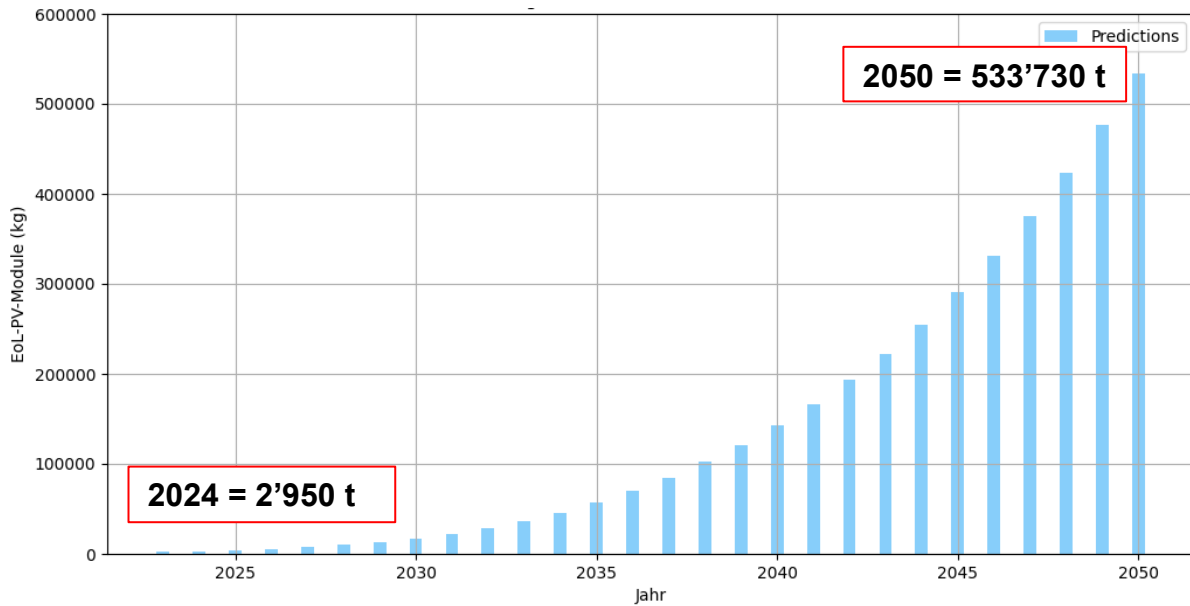


Figure 8: Forecast according to Irena and Wambach Consulting (2022).

For the calculation of the shape parameters for the Weibull curve, collection data from various countries such as France, Italy, Belgium and the Netherlands were used in further studies<sup>26</sup>. However, it should be noted that these studies were carried out almost 10 years ago and therefore the basic assumptions and base data taken into account in them also originated from this period. Furthermore, the figures for Switzerland were derived from the pan-European context for the calculation, resulting in a total quantity of approx. 530,000 tonnes by 2050. It is not certain whether this is a cumulative value, although this would be plausible when considering the PV quantities installed in recent years. In addition, a higher initial quantity (> 2,000 tonnes) was assumed in 2023. These and other factors can have a considerable influence on the significantly (20 times) higher amount of calculated EoL volume by 2050.

*Forecast Czajkowski et al. (2022)*

The second study developed an application that allows the mass indicators and shares of different PV technologies (c-Si, a-Si, CdTe and CIGS) to be taken into account. Furthermore, the retrospective analysis of installed PV quantities from previous years since 1996 forms the basis for the projection of future PV waste quantities, taking into account an average lifespan of 25 years<sup>27</sup>. As the study did not examine Switzerland as a use case, the methodology was derived as part of WP3 taking into account the installed capacities (basis Pronovo and Swissolar) from 1996-2023 and applied with the installation figures from Swissolar<sup>28</sup>. The calculation is carried out at:

$$M_y = (C_x - C_{x-1}) * u_{x,t} * w_t \text{ where}$$

C = the installed photovoltaic capacity in MW in a specific EU country;

<sup>26</sup> Forti, Baldé, and Kuehr, "E-Waste Statistics"; Magalani et al, "Study on Collection Rates of Waste Electrical and Electronic Equipment."

<sup>27</sup> Czajkowski et al, "Prediction of the Market of End-of-Life Photovoltaic Panels in the Context of Common EU Management System."

<sup>28</sup> "Swissolar," 2025.

- $t$  = a type of photovoltaic technology;
- $y$  = one year of EoL photovoltaic waste generation;
- $x$  = the year of installation of photovoltaic systems;
- $u$  = the share of a specific PV technology in year  $x$ ;
- $w$  = a mass indicator for PV panels of various photovoltaic technologies, kg/W.

This resulted in a return volume of around 147,000 tonnes by 2050. Potential export volumes or direct reuse sales were also not taken into account in this approach.

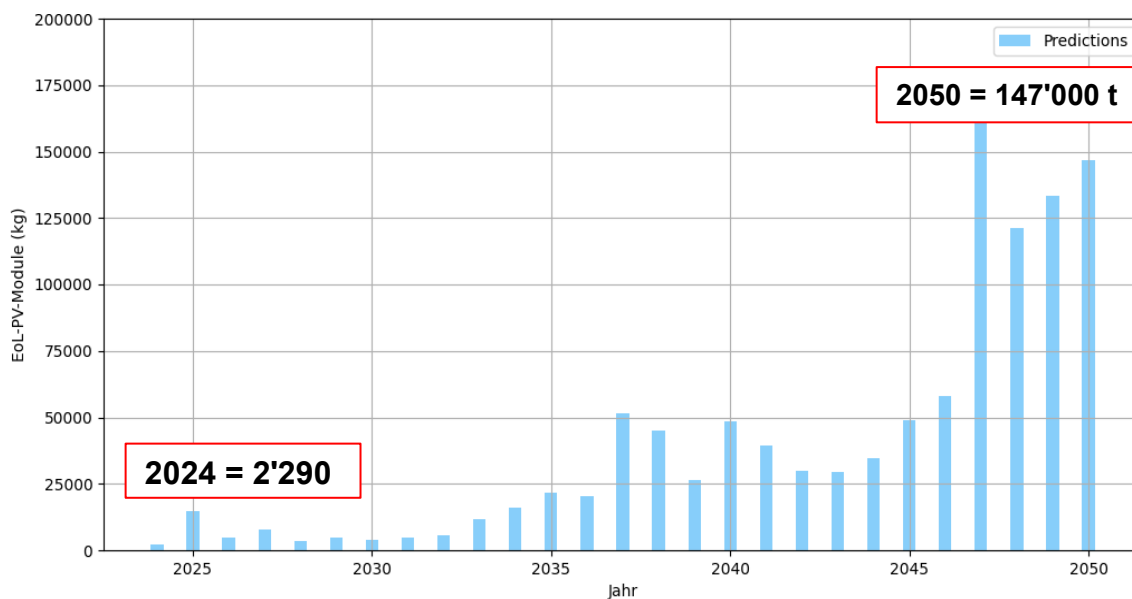


Figure 9: Forecast based on Czajkowski et al. (2022).

The three methods presented show that there are many influencing factors for the calculation of EoL quantities, but in some cases insufficient data is available. In principle, it can be assumed that a quantity of 533,000 tonnes by 2050 is very high, considering that only around 40,000 tonnes (taking into account a total installation capacity of 489,862 kWp and an estimated 20 kg/module of 250 Wp) were installed in 2024. It can therefore be assumed that a realistic value is between around 20,000 and 100,000 tonnes, whereby various factors, such as a strongly fluctuating module weight and increasing efficiencies, can significantly influence this value. In addition, there are considerable export volumes, which may tend to increase further in the coming years<sup>29</sup>. However, as none of the approaches presented allow for a projection that is as realistic as possible, it is important to identify the effective EoL quantities. For this reason, a machine learning approach was also used, which enables a probability-based classification of EoL plants in the data set created. This ML model provides the basis for identifying further EoL facilities in order to be able to make an improved estimate of EoL volumes. To this end, it is crucial to understand the characteristics of dismantled facilities and derive patterns for the model. To this end, a qualitative analysis was first carried out.

<sup>29</sup> Hansen et al, "The Dark Side of the Sun: Solar e-Waste and Environmental Upgrading In."

## 4. Discussion of the results

The results listed above make it clear that forecasting EoL plants depends on many factors, including a comprehensive and high-quality historical data basis. A great deal of effort was invested in developing a good basic inventory of EoL plants in order to be able to make initial statements about the characteristics of these plants. The Kaplan-Meier analysis in particular showed that current EoL modules have not usually reached the end of their technical service life, but can be categorised as early failures. This is particularly true for systems that enter the waste stream in the first two years of installation. Material defects, production errors and foreseeable damage can influence this shortened service life<sup>30</sup>. Furthermore, our results show that hail in particular will have an increasing influence on PV damage, firstly because extreme weather events will tend to increase, and secondly because more and more area is being covered with PV systems<sup>31</sup>. Economic factors can motivate the premature replacement of PV modules (repowering) after the first 7 - 10 years, which is consistent with the results of existing studies on economic lifetime<sup>32</sup>. This illustrates the relevance of political incentives to promote the longest possible product lifetime.

Furthermore, an exemplary projection of future EoL volumes was carried out on the basis of past collection volumes and compared with existing studies<sup>33</sup>. In a further step, additional EoL plants were classified in the data set and projected into the future using a regression model.

Basically, it can be said that a forecast is limited due to the current data situation and the timeliness and quality of this data. The results show slight to strong deviations from existing studies, of which the Weibull method<sup>34</sup> and a self-developed approach based on installed PV quantities<sup>35</sup> were analysed. However, these studies refer to several assumptions, such as an average lifetime of 25 or 30 years, and historical data from different countries, which should be updated and do not include Switzerland in these considerations. For this reason, an important step for improved forecasting is to establish a comprehensive identification of EoL plants based on characteristic features. The logistic regression model developed for this purpose at offers a suitable starting point for adding further EoL instances to the data set in future and optimising the accuracy of the model.

With this initial data basis, decision-making aids can be developed in the future to support companies involved in the circular economy in making early reuse decisions. An initial approach has already been developed within WP3 together with SENS eRecycling, whereby future collection orders could integrate pre-sorting to enable triage between reuse and recycling. Factors that were developed in collaboration with the other work packages as relevant for the reuse decision represent relevant ramifications. For example, larger PV systems (e.g. with an installation capacity of over 30 kWp) are more suitable for reuse, as the modules to be tested have a similar history and therefore residual power and quality. The condition of the PV modules is also

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<sup>30</sup> Aghaei et al, "Review of Degradation and Failure Phenomena in Photovoltaic Modules."

<sup>31</sup> Rabaia, Semeraro, and Olabi, "Recent Progress towards Photovoltaics' Circular Economy"; Gupta et al, "Impact of Hailstorm on the Performance of PV Module: A Review."

<sup>32</sup> Sodhi et al, "Economic Lifetimes of Solar Panels."

<sup>33</sup> Forti, Baldé, and Kuehr, "E-Waste Statistics"; Magalani et al, "Study on Collection Rates of Waste Electrical and Electronic Equipment"; Weckend, Wade, and Heath, "End of Life Management"; Czajkowski et al, "Prediction of the Market of End-of-Life Photovoltaic Panels in the Context of Common EU Management System."

<sup>34</sup> Forti, Baldé, and Kuehr, "E-Waste Statistics"; Magalani et al, "Study on Collection Rates of Waste Electrical and Electronic Equipment"; Weckend, Wade, and Heath, "End of Life Management."

<sup>35</sup> Czajkowski et al, "Prediction of the Market of End-of-Life Photovoltaic Panels in the Context of Common EU Management System."

relevant for the decision. While optically intact modules are potentially suitable for a second life, intact modules should go straight into the waste stream to minimise unnecessary testing costs.

However, these findings also provide policy makers with important impetus for the future development of legislation and standards. On the one hand, our study shows that improved data management is an important driver of the circular economy, as improved information on EoL products is a relevant factor for the cost efficiency of circular business models. It also shows that regulatory incentives for the most sustainable (extended) use of PV systems are relevant in order to counteract premature switching. Furthermore, there is a need for intensified education of players in the solar industry in order to promote reuse activities early in the value chain, preferably before dismantling.

## 5. Outlook and conclusion

The initial results, which were developed as part of the 'Swiss PV Circle' project, provide the starting point for further analyses. In the future, forecasting should be expanded to include new EoL systems in order to enable a more efficient estimation of EoL volumes based on more precise figures for current returns. In addition, systemic adjustments should improve data management with regard to the circular economy in the future. A detailed framework of recommendations was developed for this purpose as part of WP1. The current results are still based on a small number of EoL systems that were developed within the project. With further endeavours, supported by data analysis techniques, this inventory is to be expanded to enable more precise statements to be made.

## Appendix

### Appendix 1: Final calculated values for annual PV end-of-life volumes 2024 - 2050, based on logistic regression.

No.	Year	Total tonnes
0	2024	7178.42
1	2025	8614.86
2	2026	10191.28
3	2027	11907.67
4	2028	13764.03
5	2029	15760.37
6	2030	17896.67
7	2031	20172.95
8	2032	22589.20
9	2033	25145.42
10	2034	27841.61
11	2035	30677.78
12	2036	33653.91
13	2037	36770.02
14	2038	40026.10
15	2039	43422.15
16	2040	46958.18
17	2041	50634.17
18	2042	54450.14
19	2043	58406.08
20	2044	62501.99
21	2045	66737.87
22	2046	71113.73
23	2047	75629.55
24	2048	80285.35
25	2049	85081.12
26	2050	90016.86

## Literature

- Aghaei, M., A. Fairbrother, A. Gok, S. Ahmad, S. Kazim, K. Lobato, G. Oreski, et al. "Review of Degradation and Failure Phenomena in Photovoltaic Modules." *Renewable and Sustainable Energy Reviews* 159 (May 1, 2022): 112160. <https://doi.org/10.1016/j.rser.2022.112160>.
- Altman, Douglas G. *Practical Statistics for Medical Research*. New York: Chapman and Hall/CRC, 1990. <https://doi.org/10.1201/9780429258589>.
- BAZG, Federal Office for Customs and Border Security. "Federal Office for Customs and Border Security." Accessed January 9, 2025. <https://www.bazg.admin.ch/bazg/de/home.html>.
- Czajkowski, Adrian, Agata Wajda, Nikolina Poranek, Shubhangi Bhadoria, and Leszek Remiorz. "Prediction of the Market of End-of-Life Photovoltaic Panels in the Context of Common EU Management System." *Energies* 16, no. 1 (January 2023): 284. <https://doi.org/10.3390/en16010284>.
- Forti, Vanessa, Kees Baldé, and Ruediger Kuehr. "E-Waste Statistics," 2018. [https://collections.unu.edu/eserv/UNU:6477/RZ\\_EWaste\\_Guidelines\\_LoRes.pdf](https://collections.unu.edu/eserv/UNU:6477/RZ_EWaste_Guidelines_LoRes.pdf).
- Goel, ManishKumar, Pardeep Khanna, and Jugal Kishore. "Understanding Survival Analysis: Kaplan-Meier Estimate." *International Journal of Ayurveda Research* 1, no. 4 (2010): 274. <https://doi.org/10.4103/0974-7788.76794>.
- Goodwin, Paul, JKeith Ord, Lars-Erik Öller, Janet A. Sniezka, and Mike Leonard. "Principles of Forecasting: A Handbook for Researchers and Practitioners." *International Journal of Forecasting* 18, no. 3 (2002): 468-78. [https://doi.org/10.1016/S0169-2070\(02\)00034-1](https://doi.org/10.1016/S0169-2070(02)00034-1).
- Gupta, Vinay, Madhu Sharma, Rupendra Pachauri, and K N Dinesh Babu. "Impact of Hailstorm on the Performance of PV Module: A Review," March 31, 2022.
- Hansen et al. "The Dark Side of the Sun: Solar e-Waste and Environmental Upgrading In," 2022. <https://www.taylorfrancis.com/chapters/edit/10.4324/9781003259084-3/dark-side-sun-solar-waste-environmental-upgrading-grid-solar-pv-value-chain-ulrich-elmer-hansen-ivan-nygaard-mirko-dal-maso>.
- Hyndman, Rob J., and George Athanasopoulos. *Forecasting: Principles and Practice*. OTexts, 2018.
- Magalani, Federico, Feng Wang, Jaco Huisman, and Ruediger Kuehr. "Study on Collection Rates of Waste Electrical and Electronic Equipment," 2014. [https://ec.europa.eu/environment/pdf/waste/weee/Final\\_Report\\_Art7\\_publication.pdf](https://ec.europa.eu/environment/pdf/waste/weee/Final_Report_Art7_publication.pdf).
- Makridakis, Spyros, S. Wheelwright, and Rob Hyndman. "Forecasting: Methods and Applications." In *The Journal of the Operational Research Society*, Vol. 35, 1984. <https://doi.org/10.2307/2581936>.
- Opendata.Swiss. "Electricity Production Plants - Opendata.Swiss," 2024. <https://opendata.swiss/en/dataset/elektrizitatsproduktionsanlagen>.
- Patton, M. Q. "Enhancing the Quality and Credibility of Qualitative Analysis." *Health Services Research* 34, no. 5 Pt 2 (December 1999): 1189.
- Prinja, Shankar, Nidhi Gupta, and Ramesh Verma. "Censoring in Clinical Trials: Review of Survival Analysis Techniques." *Indian Journal of Community Medicine : Official Publication of Indian Association of Preventive & Social Medicine* 35, no. 2 (April 2010): 217-21. <https://doi.org/10.4103/0970-0218.66859>.
- Rabaia, Malek Kamal Hussien, Concetta Semeraro, and Abdul-Ghani Olabi. "Recent Progress towards Photovoltaics' Circular Economy." *Journal of Cleaner Production* 373 (November 1, 2022): 133864. <https://doi.org/10.1016/j.jclepro.2022.133864>.
- Ragab, Ahmed, Mohamed-Salah Ouali, Soumaya Yacout, and Hany Osman. "Remaining Useful Life Prediction Using Prognostic Methodology Based on Logical Analysis of Data and Kaplan-Meier Estimation." *Journal of Intelligent Manufacturing* 27, no. 5 (October 1, 2016): 943-58. <https://doi.org/10.1007/s10845-014-0926-3>.
- SENS eRecycling. "Recycling system for photovoltaics in Switzerland." SENS eRecycling, 2024. <https://www.erecycling.ch/wissenswertes/wissensblog/fach-94.html>.
- Sodhi, Manbir, Lennart Banaszek, Chris Magee, and Mercedes Rivero-Hudec. "Economic Lifetimes of Solar Panels." *Procedia CIRP*, The 29th CIRP Conference on Life Cycle Engineering, April 4 - 6, 2022, Leuven, Belgium, 105 (January 1, 2022): 782-87. <https://doi.org/10.1016/j.procir.2022.02.130>.
- Stoltzfus, Jill C. "Logistic Regression: A Brief Primer." *Academic Emergency Medicine* 18, no. 10 (2011): 1099-1104. <https://doi.org/10.1111/j.1553-2712.2011.01185.x>.
- Subasi, Abdulhamit. *Practical Machine Learning for Data Analysis Using Python*. Academic Press, 2020.
- "Swissolar," 2025. <https://www.swissolar.ch/de/angebot/veranstaltungen/vortraege-und-studien>.
- "Swissolar," 2025. <https://www.swissolar.ch/de>.
- Thomas, David R. "A General Inductive Approach for Qualitative Data Analysis," 2003.
- Weckend, Stephanie, Andreas Wade, and Garvin A. Heath. "End of Life Management: Solar Photovoltaic Panels." Paris, France: International Energy Agency (IEA), June 1, 2016. <https://doi.org/10.2172/1561525>.
- Widodo, Achmad, and Bo-Suk Yang. "Application of Relevance Vector Machine and Survival Probability to Machine Degradation Assessment." *Expert Systems with Applications* 38, no. 3 (March 1, 2011): 2592-99. <https://doi.org/10.1016/j.eswa.2010.08.049>.