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Research Paper

Forecasting waste from key energy transition technologies in Italy

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ABSTRACT

The global energy transition towards renewable and electrified systems is rapidly driving material demand, particularly for critical raw materials (CRMs) embedded in low-carbon technologies. While enabling decarbonization, these systems remain largely based on linear material flows, in which increasing volumes of primary resources are deployed and ultimately discarded, creating emerging risks related to waste management, resource security, and missed circular economy opportunities. By mid-century, end-of-life material streams from energy transition technologies are expected to increase by orders of magnitude, highlighting the need for robust quantification, for proper waste management planning and recovery.

This study estimates future end-of-life materials in Italy from four key technologies: lithium-ion batteries from electric vehicles and stationary energy storage systems, electric motors from electric vehicles, photovoltaic panels, and wind turbine blades. Projections are obtained using a dynamic sales-stock-lifespan model combining historical and scenario-based inflows with technology-specific Weibull lifetime distributions, aligned with Italy's climate neutrality pathways. Results indicate a sharp growth in annual waste flows from 2030 to 2050. Battery waste increases from approximately 27 kt in 2030 to 551–736 kt by 2050, electric motors waste rises from 6 kt in 2030 to 86 in 2050, photovoltaic panel waste from 81 to 88 kt to 245–269 and wind turbine blades waste from 8 kt to 16. Across all technologies, the projected end-of-life flows will contain approximately 390–510 kt of critical raw materials by 2050, representing a substantial secondary resource potential. The findings support planning for treatment capacity, regulatory traceability, second-life strategies, and advanced recycling pathways.

1. Introduction

The energy transition towards climate neutrality is reshaping energy systems and accelerating the deployment of material-intensive low-carbon technologies. As these technologies will inevitably reach their end of life (EoL) in the coming years, the objective of this study is to quantify the magnitude and timing of waste flows that will require adequate collection, treatment, and recycling infrastructure in the coming decades. These technologies rely heavily on critical raw materials (CRMs), many of which face import dependency and increasing supply risks, raising concerns over long-term resource security and affordability of clean energy technologies.

Therefore, beyond a waste-management issue, EoL energy transition technologies constitute a secondary resource reservoir whose proper management can recover significant quantities of CRMs and reduce dependence on primary supply.

This study analyses four waste streams: Li-ion batteries from electric vehicles (EVs) and battery energy storage systems (BESSs), electric motors from EVs, photovoltaic (PV) panels, and wind turbine blades (WTBs). Together, these technologies represent the core pillars of electrification and decarbonisation and account for the majority of installed capacity and material demand within the energy transition (IEA, 2023).

Previous studies have estimated future waste flows for individual technologies, but they are generally conducted in isolation and rely on heterogeneous modelling assumptions. Consequently, integrated assessments using a consistent methodology remain limited, constraining waste-management planning.

Studies on forecasting waste flows from EV batteries (Table S1) cover various geographical regions, with only one recent project conducted in Italy by Motus-E (2023). PV waste projections have been developed for

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multiple countries and regions, including Italy (Paiano, 2015; Franzoni et al., 2024) (Table S9). Since EoL WTBs are still challenging to recycle, in the literature several studies (Table S14) provide Europe-wide or country-specific estimations of the waste resulting from the installed capacity.

Across the literature, approaches differ substantially in lifetime modelling and mass estimation. Studies rely on deterministic fixed-lifetime approaches for EVs (Drabik & Rizos, 2018), or PVs (Paiano, 2015), or on stochastic lifetime distributions for EVs (Huster et al., 2022), PVs (Mahmoudi et al., 2019) and WTBs, for which normal (Lahuerta et al., 2023; Sommer et al., 2020), logistic (Lichtenegger et al., 2020), or Weibull distributions calibrated on decommissioning data (Abrahamsen et al., 2024; Johst et al., 2024) are found. Similarly, mass estimation methods range from fixed battery weight (Bruno and Fiore, 2023; Volan et al., 2021), to vehicle- and chemistry-dependent models (Wu et al., 2020; Shafique et al., 2023) and PV cell technologies (Mahmoudi et al., 2019) and time-dependent weight-to-power ratios (Sharma et al., 2024). Methods for estimating WTB mass vary considerably, spanning average weight-per-capacity ratios (Liu & Barlow, 2017), regressions based on rated power or rotor length (Lichtenegger et al., 2020), and manufacturer-specific data (Lahuerta et al., 2023). This methodological heterogeneity limits cross-technology comparability and national-level planning. To address this gap, this study performs a joint assessment of four energy-transition waste streams using a unified predictive modelling framework, while preserving technology-specific characteristics. In addition to waste quantities (Nabi & Nema, 2024), the analysis characterises future waste composition, including battery chemistries, motor types, PV technologies, and CRM content. The model integrates updated Italian deployment data and literature-based parameters to improve projection robustness.

In this context, this study aims to (i) estimate EoL volumes of four selected technologies up to 2050 (and qualitatively beyond) under Italian decarbonisation scenarios; (ii) evaluate recoverable materials, particularly CRMs, embedded in these waste streams; and (iii) discuss the implications for recycling capacity, regulatory frameworks, and circular waste management and treatment strategies.

The work constitutes a quantitative basis to support planning for upcoming waste streams from energy-transition technologies.

2. Materials and methods

In this section, the methodology and the data used to forecast the amount of EoL materials for each technology are discussed. Also, the specific assumptions for modelling the four selected flows and applying the general modelling framework to Italy are reported.

2.1. Forecasting waste flows

Forecasting EoL flows from rapidly evolving energy-transition technologies is challenging due to limited historical data, changing product designs, and heterogeneous lifetimes (Koshta et al., 2021). Various modelling approaches have been used in the literature, including stock-driven material flow analysis (MFA), time-step methods, and different lifetime-distribution approaches (Nabi & Nema, 2024). In this study, the sales-stock-lifespan (SS-L) model is adopted to estimate the four waste streams, thanks to the availability of data on sales, stock and lifespan. This approach enables a comprehensive quantification of EoL flows by capturing the dynamic relationship between market deployment and discard behaviour over time (Ambarwati et al., 2024), which is best represented through the Weibull probability distribution, as recommended by the EU Implementing Regulation 2017/699 (European Commission, 2017). The SS-L model generates an output flow (waste) by combining the annual inflows (i.e. vehicle registrations or installed power capacity), derived from historical records and scenario projections, with a lifetime distribution for each technology. The lifetime distribution is represented by a Weibull probability density function (PDF), which describes the probability that a unit reaches the EoL as a function of time since installation or sale. The Weibull probability distribution is characterised by two parameters: shape and scale (Tan & Li, 2014). The scale parameter (λ) represents the average lifetime of a product (Sanclemente Crespo et al., 2022; Sharma et al., 2024), while the shape parameter (k) controls the failure rate profile over time (Rettenmeier et al., 2025). For each technology, the scale and shape parameters were specifically selected (see sections 2.3, 2.4, 2.5, 2.6). Hence, for a given technology, the annual EoL outflow in year t is obtained by discrete convolution (applied through MATLAB) of the annual input time series with the Weibull PDF as shown in Eq. (1).

$$EoL\,(t) = \sum\nolimits_{j=1}^{t} W(t-j+1) \bullet input(j) \tag{1}$$

$W(t-j+1)$ is the Weibull PDF evaluated at time $t-j+1$; j is the index of the year of sale or installation; the term $t-j+1$ reflects the age of products sold or installed in year j when evaluated in year t; $input(j)$ refers to the quantity of product coming into operation in year j.

The analysis timeframe starts in 1992 for technologies with longer deployment histories (PV and wind energy) and in 2005 for EV-related technologies (batteries and motors). Projections extend to 2050, consistent with EU and Italian climate neutrality targets, while modelled EoL flows continue beyond mid-century according to product lifetimes.

2.2. Scenario-based modelling and material composition assumptions

Future inflows for the four technologies can be driven by national climate and energy scenarios, up to 2050. For Italy, two main sources are used. The short-term scenario reflects the Integrated National Energy and Climate Plan (INECP), a strategic plan updated in June 2024 (Ministero dell'Ambiente e della Sicurezza Energetica, 2024) that defines Italy's energy and climate targets for 2030, including increased energy efficiency, reduced greenhouse gas emissions and expanded renewable capacity. The INECP is Italy's legally binding national energy and climate plan under EU Regulation (EU) 2018/1999. The long-term scenarios, instead, rely on those described in the "Document of scenarios description" (DDS) by Terna and SNAM (2024), which supports planning of electricity and gas infrastructure to 2040. The Terna–SNAM DDS 2024 is an official regulatory planning tool for national electricity and gas infrastructure development; this set of scenarios provide robust and policy-aligned foundation for modelling future technology diffusion. This document introduces two scenarios of climate neutrality to be reached by 2050: Distributed Energy Italy (DE-IT), centred on widespread electrification and extensive deployment of wind and solar, with limited hydrogen use in hard-to-abate sectors, and Global Ambition Italy (GA-IT), which relies on broad hydrogen integration and carbon capture and storage (CCS), particularly in hard-to-abate industries and thermoelectric generation. The scenarios used in the SS-L model can be summarised as follows. By 2030, the Italian INECP foresees an EV stock of 4.3 million battery electric vehicles (BEVs) and 2.2 million plug-in hybrid electric vehicles (PHEVs), a BESS capacity of 72 GWh, a PV installed capacity of 80 GW, and a wind energy capacity of 26 GW onshore and 2.1 GW offshore. By 2040, the DE-IT scenario projects higher EV stocks (14.3 million BEVs and 3.3 million PHEVs), BESS capacities reaching 166.5 GWh, PV capacities of 121 GW, and wind deployment up to 34 GW onshore and 15.1 GW offshore. The GA-IT scenario projects, by 2040, 11.7 million BEVs and 3.3 million PHEVs, BESS capacity of 133.6 GWh, PV capacity of 111 GW, 31 GW of onshore wind and 12.1 GW offshore.

For each technology, the future inflow to reach the targets is modelled as a logistic (S-curve) growth of EV stock or cumulative capacity, consistent with innovation diffusion theory (Fluchs, 2020; Rogers, 1962). The logistic function (Eq. (2)) describes the cumulative amount P over time t, as a function of K, which is the upper saturation limit (linked to decarbonisation targets), r, which is the growth rate calibrated to meet 2030 and 2040 targets, and P_0, which is the initial amount of product.

$$P(t) = \frac{P_0 K e^{rt}}{K - P_0 + P_0 e^{rt}} \quad (2)$$

From the cumulative logistic curve, annual inflows are derived as year-on-year differences. This approach reflects the typical pattern of technology uptake: slow initial diffusion, rapid growth as the technology becomes mainstream, and saturation at high penetration levels.

Taken together, the logistic trajectories (Fig. S3, Fig. S4, Fig. S5, Fig. S11, Fig. S16, Fig. S17) provide coherent inflows for all four technologies, ensuring that waste forecasts are consistent with Italy's decarbonisation pathways.

Once the total EoL quantities for the four technologies are estimated by applying the Weibull PDF described in 2.1, the analysis shifts to the contained raw materials, particularly CRMs, which could be recovered through recycling.

For each energy transition technology, the material composition is analysed, and the CRMs are highlighted. The material composition of each battery chemistry, electric motor, and wind turbine blade is assumed to remain constant over the period considered (2005–2050 for batteries and motors, 1992–2050 for blades). However, for batteries, the temporal evolution of the market shares of different battery chemistries is considered. For PV panels, not only the market shares of PV cell technologies, but also the composition is varied over time, reflecting technological developments in the PV module manufacturing.

2.3. Model details for Li-ion batteries

The battery model is developed for Li-ion batteries used in passenger cars, BEVs and PHEVs, light-commercial vehicles (LCVs), and BESSs. Historical EV registrations in Italy from 2005 to 2024, disaggregated by powertrain type (BEV, PHEV and LCV), are used as inflows (UNRAE, 2025). LCVs are included only in the historical dataset (up to 2024); their future evolution is not modelled, as the scenarios define targets exclusively for BEVs and PHEVs. The lifetime of EV batteries is represented by a Weibull distribution with a scale parameter λ equal to 12 years of average lifetime and a shape parameter k equal to 3.5 (Shafique et al., 2022), which approximates a normal distribution of service life (Rettenmeier et al., 2025). The model can be validated by comparing the number of estimated EoL EVs with data of de-registered EVs (Fig. S1), with a coefficient of determination, or R-squared, equal to 0.7, which is acceptable despite the limited amount of real-world data.

Second-life reuse is explicitly represented through a cascade-use stock approach. A time-dependent reuse rate is applied to EoL EV batteries: 0% before 2030, 10% in 2030, increasing linearly to 50% in 2050. 50% reuse rate was adopted by previous studies by ICCT (Tankou et al., 2023) and Shafique et al. (2022). EoL vehicles' batteries are preferably not disposed of but rather diverted to supply part of the stationary BESS demand (Volan et al., 2021; Aeroporti di Roma (n.d.)). The remaining demand is met by newly manufactured batteries. The two BESS flows (i.e. repurposed and new batteries) are modelled separately using Weibull lifetime distributions: $\lambda = 10$ years for second-life batteries (Tankou et al., 2023) and $\lambda = 14$ years for new BESS units (Terna, 2023), and their EoL outputs are subsequently summed. When the available second-life capacity exceeds BESS demand, the surplus is directly accounted for as EV battery waste. This formulation preserves mass balance and introduces the temporal delay associated with cascade utilisation.

Future EV registrations for the period 2025–2050 are obtained from logistic curves (Fluchs, 2020; Marchetti, 1983; Rietmann et al., 2020; Ruoso & Ribeiro, 2022) calibrated to match the stock targets defined in the INECP, DE-IT and GA-IT scenarios. The P_0 parameter, which is the initial amount of EVs, in 2024, is equal to 258,481 BEVs, and 250,505 PHEVs (the total EVs registered up to 2024); K is set to twice the target value of 2040, under the assumption that by the target year, the EV stock will have reached half of its saturation level. This assumption is reasonable, given that the current stock of vehicles in Italy is around 41 million and that the transport sector will need to be fully decarbonised. Finally, the Excel solver tool is used to calibrate the parameter r, enabling to reach the target.

To convert the number of EVs into mass flows, EV and BESS inflows are disaggregated by cathode chemistry, i.e. nickel-manganese-cobalt (NMC), lithium iron phosphate (LFP) and lithium manganese iron phosphate (LMFP), according to historical and projected market shares, using data from Transport & Environment (2024) (Fig. S2). The temporal evolution of battery chemistries shows the future predominance of LFP, with a consequent reduction of cobalt demand for batteries. For each year and each chemistry, the model calculates the EoL battery capacity in kWh, by multiplying the number of EVs by the average pack capacity, assumed to be 60 kWh for BEVs and LCVs and 15 kWh for PHEVs, based on IEA (2024). Then, the EoL battery capacity is divided by the chemistry-specific energy density, 200 Wh/kg for NMC, 143 Wh/kg for LFP and 180 Wh/kg for LMFP, using data from Argonne National Laboratory (2024), Evro et al. (2024) and Zhao (2023). This procedure yields annual mass flows in kilotonnes per year for each chemistry. An analogous approach is applied to stationary BESSs.

A sensitivity analysis was conducted to assess how variations in battery lifetime and reuse rate affect the projected amount of battery waste (Fig. S7, Table S2, Table S3).

2.3.1. Li-ion batteries composition

To estimate the potentially recoverable materials from EoL batteries, the structure of a lithium-ion battery is analysed. The battery consists of multiple cells assembled into a pack. Each cell includes an anode, usually graphite (only seldom silicon-graphite), a cathode, generally a lithium metal oxide, and an electrolyte. The anode and cathode account for most of the critical material used in the battery (IRENA, 2024). CRMs are lithium, cobalt, nickel, manganese, phosphorus present in the active cathode material, graphite and copper used in the anode, lithium in the electrolyte ($LiPF_6$), and aluminium used in casing and wiring.

The overall material composition of lithium-ion batteries is retrieved from Winjobi et al. (2020), whereas the cathode material compositions from Maisel et al. (2023) and they are reported in Table S4 and Fig. S8, respectively, of the supplementary material.

2.4. Model details for electric motors

To estimate the EoL flow of electric motors, it is assumed that each EV contains one single motor (Tazi et al., 2023), and annual motor inflows follow EV registrations under the same diffusion scenarios used for batteries. The SS-L model adopts the same Weibull lifetime parameters as for Li-ion batteries (average lifetime of 12 years, shape parameter 3.5), but without a reuse rate, since no second-life practice is considered. The mass of motors in kt per year is calculated using the distribution of motor technologies in the market, about 85% permanent-magnet motors (PM), 12% alternated-current induction (ACIM), and 3% wound-rotor synchronous motors (WRSM) (IDTechEx, 2024). Average masses are 44.9 kg for PM motors in BEVs, 48.8 kg for PM-free motors in BEVs, and 34.5 kg for PM motors in PHEVs (Tazi et al., 2023).

A sensitivity analysis explores how changes in EV lifetime affect projected waste (Fig. S9, Table S7).

2.4.1. EV motors composition

The material composition (Fig. S10) is dominated by electrical steel, aluminium and copper, which are found in both PM and PM-free motors, while CRMs, including boron, neodymium, praseodymium and dysprosium, are contained in permanent magnets (Carrara et al., 2020). Electrical steel, which is a ferritic iron-silicon alloy (Garrison, 2001), contains silicon (another CRM). PM-free motors (ACIM, WRSM) contain almost no CRMs and have a smaller market share (IDTechEx, 2024).

2.5. Model details for PV panels

The SS-L model is applied to the installed PV capacity. Historical inflow data consist of annual PV installations and cumulative capacity in Italy from 1992 to 2024 (37 GW) as reported by IRENA (de l'Epine & Kaizuka, 2024), while future additions up to 2050 are generated through logistic curves calibrated to the INECP 2030 targets and the DE-IT and GA-IT trajectories for 2040 (Fig. S11). For the logistic trajectory, P_0 is assumed equal to the total installed capacity in 2024, K equal to 300 GW, which is the decarbonisation target set by the Italian long-term strategy document (Ministero dell'Ambiente e della Tutela del Territorio e del Mare et al., 2021), and r is calibrated using the solver tool on Excel to satisfy the strategic target.

Lifetime modelling is based on a Weibull distribution with a scale parameter of 25 years, as the average module lifetime (Franzoni et al., 2024). Two sets of shape parameters are used: an early-loss scenario, characterised by a shape value of 2.49, capturing failures linked to defects, transport or installation, and a regular-loss scenario, with a shape value of 5.37, focused on wear-out failures (IEA, 2016).

To convert capacity into mass, installed capacity is disaggregated by cell technology: mono-crystalline and multi-crystalline silicon, amorphous silicon, cadmium telluride (CdTe), and copper indium gallium selenide (CIGS). The partitioning is based on historical and projected market shares from national statistics (Gestore dei Servizi Energetici S.p.A, 2025) and international sources (Fraunhofer and PSE Projects GmbH, 2024; IEA, 2021) (Fig. S12). A weight-to-power ratio (kg/W_p) is applied to each technology, using historical values up to 2010 by Monier and Hestin (2011) and projected values for 2010–2050 (Carrara et al., 2020) (Table S10). This procedure yields annual installed mass for each PV technology, which is then combined with the lifetime distribution to obtain EoL mass flows.

Model validation is performed by comparing the estimated EoL PV mass with Eurostat data on collected PV waste in Italy for the period 2018–2022 (Eurostat, 2025). The resulting coefficient of determination of about 0.49 is due to limited data, nonetheless the model reproduces the overall trend (Fig. S13).

A sensitivity analysis explores how changes in average lifetime affect the results (Fig. S14, Table S11).

2.5.1. PV modules composition

To calculate the recoverable raw materials of PV waste, the installed capacity (in MW) is multiplied by technology-specific material intensities (t/MW) from the medium-demand scenario proposed by Carrara et al. (2020). These material intensity coefficients vary across four time periods (1992–2009, 2010–2018, 2019–2030, 2031–2050), reflecting technological progress, as detailed in Table S12. Concrete and

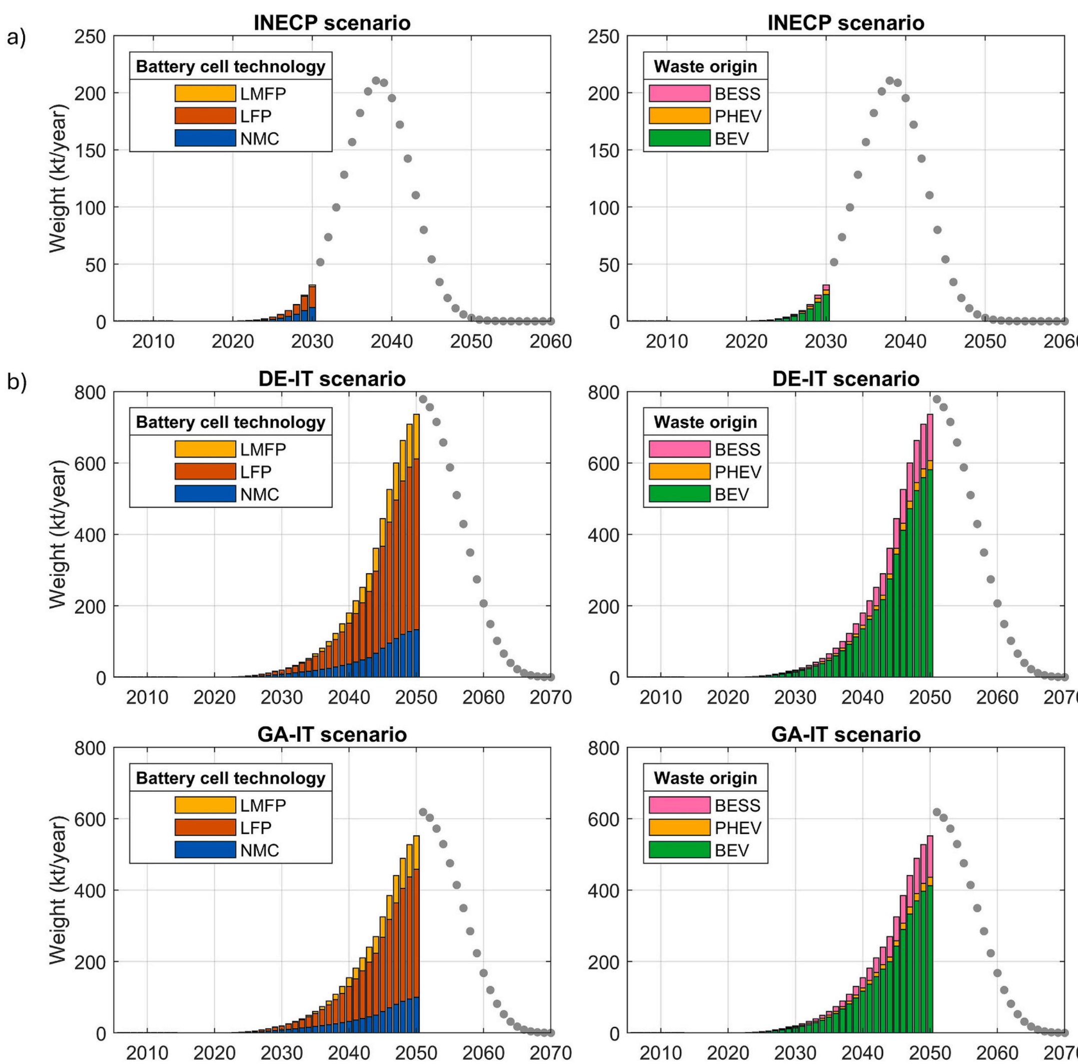

Fig. 1. Predicted Li-ion battery waste disaggregated by cell technology (nickel-manganese-cobalt, NMC, lithium iron phosphate, LFP, lithium manganese iron phosphate, LMFP) and battery origin (BEV, PHEV, BESS), in Italy, a) for short-term scenario (INECP) and b) long-term scenarios (DE-IT and GA-IT). Inflows are assumed to stop at year 2030 for INECP scenario and in 2050 for long-term scenarios.

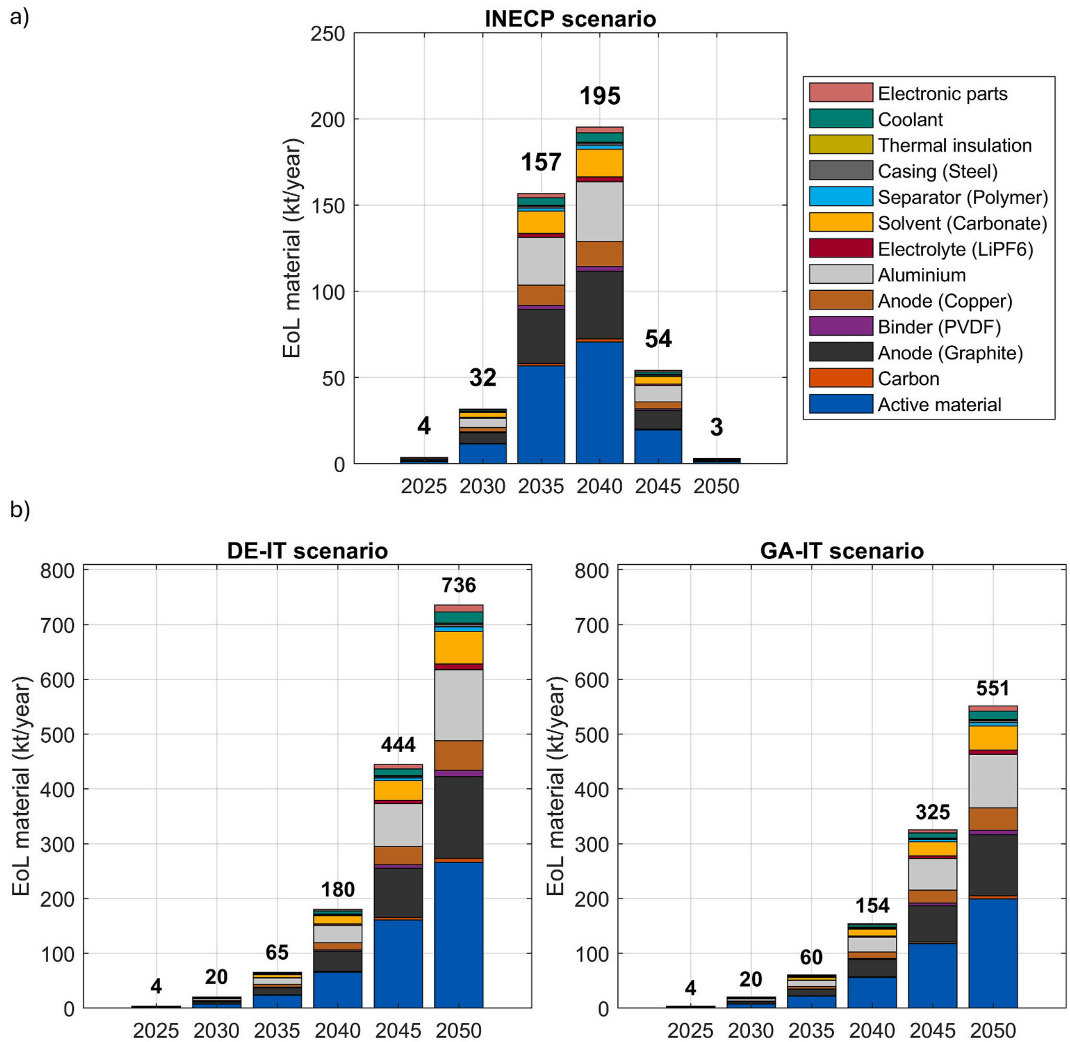

Fig. 2. Projected components and materials of EoL Li-ion batteries from EVs and BESSs, in Italy, for a) short-term scenario (INECP) and b) long-term scenarios (DE-IT and GA-IT). Inflows are assumed to stop at year 2030 for INECP scenario and in 2050 for long-term scenarios.

structural steel are excluded from the material composition as part of the balance of system of PV plants. Also, copper content is adjusted to reflect only the share contained within modules, based on IEA PVPS Life Cycle Inventory (2020), removing copper associated with wiring and other electrical components. Then, the Weibull probability density function is applied to derive the annual EoL flows, disaggregated by raw materials embedded.

2.6. Model details for wind turbine blades

Similarly to the other waste streams, this study applies the SS-L model to provide results for the Italian context, including onshore and offshore wind farms. The historical data on installations are retrieved from the dedicated wind farms database *TheWindPower*, starting from 1992 (TheWindPower, 2024). However, some data gaps and inaccuracies are identified: for 160 entries (corresponding to 2.17 GW) the commissioning date is not available and the cumulative installed capacity as of 2024 – without considering wind farms with unknown commissioning year – from the database totals 10.3 GW instead of 13 GW, i.e. the latest data provided by other sources' data (i.e. GSE and Terna statistics), thus requiring input data to be corrected starting from 2013 (Table S15). For future installations, two logistic trajectories are assumed, distinguishing between onshore and offshore deployments. The parameter P_0 is assumed equal to the cumulative installed wind capacity in 2024: 13 GW for onshore and 30 MW for offshore. The upper saturation limit K is defined differently depending on the category of wind farm. For onshore wind, constrained by land availability and expected to saturate earlier, the 2040 target is assumed to correspond to two-thirds of K (51 GW). Offshore wind, being more recent and with larger untapped potential, adopts the technical potential for Italy estimated by GWEC (2021) equal to 189 GW.

To predict the expected decommissioning date, a Weibull distribution is applied to onshore WTs, based on literature information for shape and scale parameters, since data on decommissioned WTs and plants in Italy are not available to derive specific parameters. The parameters chosen are the average lifespan (λ) equal to 20 years (Abrahamsen et al., 2024), and the scale parameter (k) equal to 6.5 (Johst et al., 2024). Offshore installations, instead, are much more recent and therefore there is no available empirical data on decommissioning to derive lifetime profile and distribution's parameters. Thus, a fixed lifetime is assumed equal to 25 years, i.e. the design lifetime of offshore wind turbines (Abrahamsen et al., 2024). A sensitivity analysis is performed to test the variability of results under different lifetime assumptions (Fig. S18, Table S16).

The determination of the mass of the WTBs reaching EoL can follow a variety of approaches, depending on the available information. For past installations with a known WT model, the information provided by the *WindTurbineModels* database (wind-turbine-models.com, 2025) is combined with the regression functions provided by Lichtenegger et al. (2020). For WTs of unknown model and future installations, linear regressions are built to estimate the average rated power depending on the year (Fig. S15). The blade mass is then derived from the rated-power regression in Lichtenegger et al. (2020).

2.6.1. Wind turbine blades composition

WT blades are mostly made of composite materials, namely a polymer resin reinforced with fibres, but also contain various other materials, e.g. the sandwich core, coatings, adhesives and metal parts (ETIPWind, 2019). In terms of reinforcing materials, glass fibre (GF) is the most common one, but carbon fibre has also been introduced by some manufacturers to partly substitute GF in the interior section of blades, to allow the construction of longer and lighter WTBs (Johst et al., 2024; Lefeuvre et al., 2019). However, due to a low level of detail of available information, it is assumed that only glass fibre is employed. The average material composition, according to ETIPWind (2019), is 85% glass-fibre reinforced plastic (GFRP), 9% core materials, 3% adhesives and coating, and 3% metals. Also, GFRP can be approximated as 60% reinforcing fibres and 40% polymer matrix (Fonte & Xydis, 2021).

3. Results

Results of the projected EoL flows are expressed in kilotonnes per year (kt $year^{-1}$) of waste generated. Note that the INECP scenario reflects inflows of new EVs and installations only up to 2030, to reach short-term targets, whereas the DE-IT and GA-IT scenarios include inflows extending up to 2050, extending the trajectories from the 2040 goals.

3.1. Li-ion batteries

In 2030, under the INECP scenario (Fig. 1), Li-ion battery waste is expected to reach 31.7 kt $year^{-1}$, split between 4.3 kt $year^{-1}$ of BESS, 23.2 kt $year^{-1}$ of BEVs and 4.2 kt $year^{-1}$ of PHEVs. Looking ahead to 2050, the DE-IT scenario forecasts 736 kt $year^{-1}$ of waste, of which 130 kt $year^{-1}$ are from BESS, 581 kt $year^{-1}$ from BEVs, and 25 kt $year^{-1}$ from PHEVs. In contrast, the GA-IT scenario shows a total of 551 kt $year^{-1}$ of waste, with 116 kt $year^{-1}$ of BESS, 412 kt $year^{-1}$ of BEVs, and 23 kt $year^{-1}$ of PHEVs. Waste generation in long-term scenarios peaks in the year 2051.

Fig. 2 shows the projected total amount of batteries reaching end-of-life in Italy every 5 years, between 2025 and 2050. The highest contributions in mass are attributable to the active cathode material, with up to around 11.4 kt $year^{-1}$ by 2030, the anode (graphite), aluminium (casing), copper (wiring), and solvent. Detailed estimates are reported in Table S5.

The CRM content of batteries is further isolated from the overall

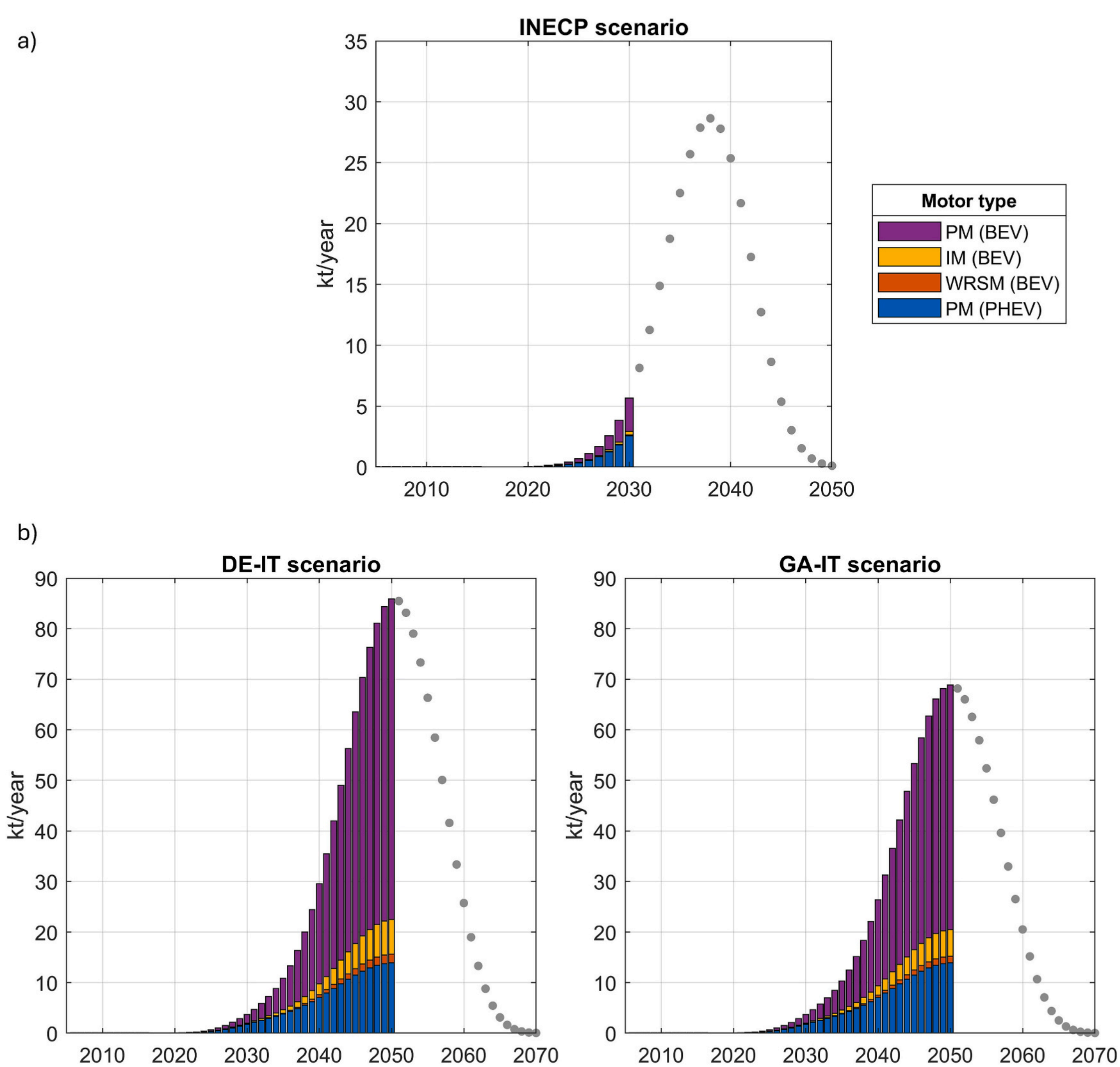

Fig. 3. Projected electric motor waste in Italy, disaggregated by motor type, for a) short-term scenario (INECP) and b) long-term scenarios (DE-IT and GA-IT). Inflows are assumed to stop at year 2030 for INECP scenario and in 2050 for long-term scenarios.

material composition (Table S6) reaching 19 kt year^{-1} by 2030 and 222–428 kt year^{-1} by 2050. Graphite (3–6 kt y^{-1} by 2030 and 112–149 kt y^{-1} by 2050), aluminium (3–5 kt y^{-1} by 2030 and 97–130 kt y^{-1} by 2050) and copper (1–2 kt y^{-1} by 2030 and 40–54 kt y^{-1} by 2050) are the largest contributors to the quantity of recoverable CRMs, although significant value is also embedded in cathode materials, i.e. lithium, cobalt, nickel, manganese and phosphorous.

3.2. Electric motors

Model projections (Fig. 3) estimate that electric motor waste will reach 6 kt year^{-1} by 2030, under the INECP scenario, and between 69 and 86 kt year^{-1} by 2050, under the long-term scenarios, GA-IT and DE-IT, respectively. The largest share of this waste is expected to come from PM motors, due to their market dominance. A sensitivity analysis shows the variability of results with variable lifetime of EVs (Fig. S9, Table S7).

The material composition of electric motors, and the generated waste (Fig. 4, Table S8) is dominated by electrical steel, with up to around 2.8 kt y^{-1} by 2030, aluminium (1–2 kt y^{-1} by 2030 and 22–27 kt y^{-1} by 2050) and copper (400–700 t y^{-1} by 2030 and 8–10 kt y^{-1} by 2050), as main material components and CRMs. High value is embedded in magnets contained in PM motors (90–100 t y^{-1} by 2030 and 1–2 kt y^{-1} by 2050).

3.3. PV panels

The projections for PV waste are reported in Fig. 5. In the INECP scenario, the projected PV panel waste in 2030 is approximately 88 kt year^{-1} under the early-loss scenario and around 81 kt year^{-1} under the regular-loss scenario. The early-loss scenario results in a more gradual progression, as reflected in the smoother shape of the waste curve compared to the regular-loss scenario. In contrast, the regular-loss scenario delays the onset of PV waste, making the peaks more pronounced due to the high capacity added in 2010 and 2024. This scenario reaches its peak waste generation in 2035, with 114 kt. In 2050, DE-IT scenario forecasts around 271 kt year^{-1} of waste under the early-loss scenario and about 269 kt year^{-1} under the regular-loss scenario. In the GA-IT scenario, waste is projected to reach approximately 245 kt year^{-1} under both the early-loss and the regular-loss scenarios. The early-loss scenario shows an anticipation of PV waste generation. The peak for the early-loss scenario is reached in 2058, whereas in the regular-loss scenario the peak is delayed to 2063.

Regarding the material composition of PV waste (Fig. 6), glass dominates the mass of PV modules, with almost 62 kt year^{-1} by 2030, representing roughly two-thirds of the total waste, while polymers and aluminium also contribute substantially. Projections indicate that CRM content in PV waste will reach 14.2–15.3 kt year^{-1} by 2030 and 24.9–43.6 kt year^{-1} by 2050 (Table S13), with aluminium providing the largest share (9–10 kt y^{-1} by 2030 and 28–31 kt y^{-1} by 2050), followed by

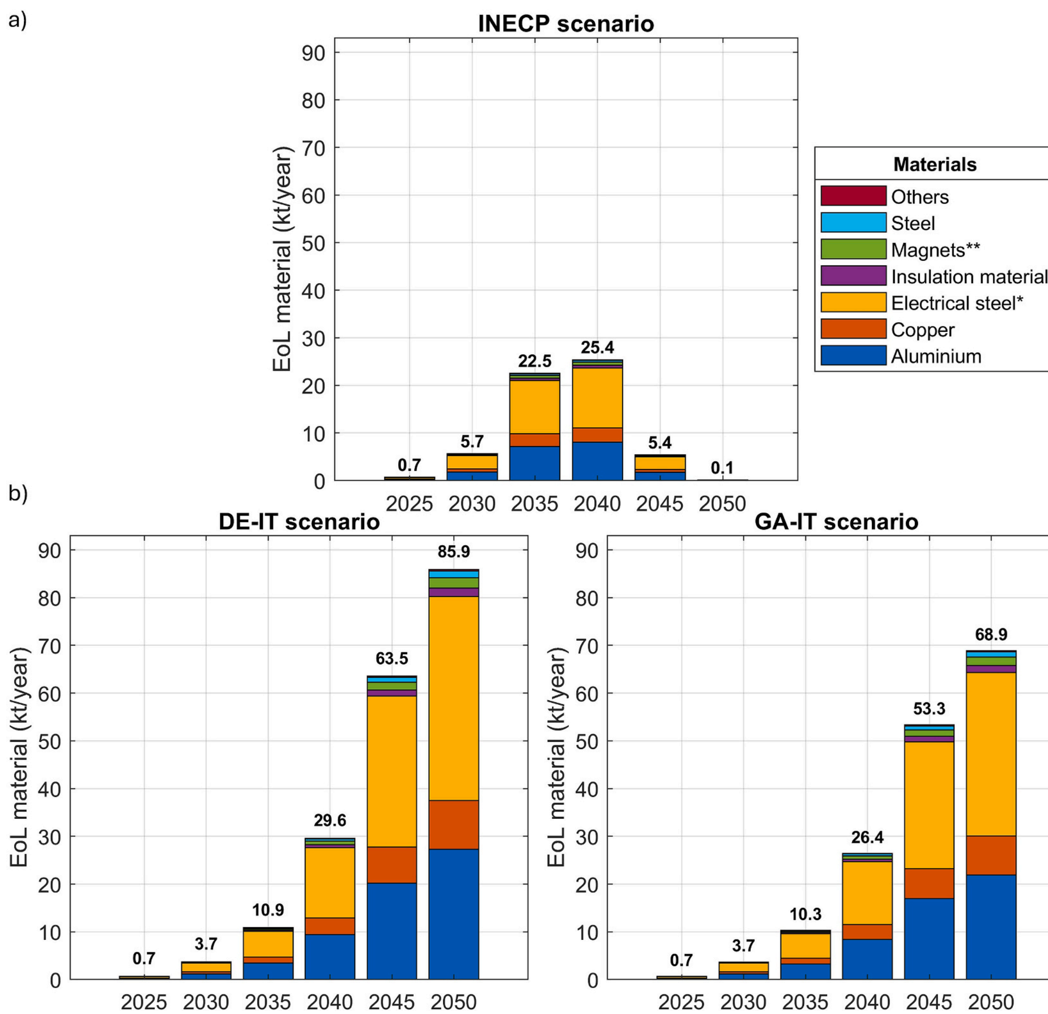

Fig. 4. Projected electric motor waste in Italy, disaggregated by material categories, for a) short-term scenario (INECP) and b) long-term scenarios (DE-IT and GA-IT). Inflows are assumed to stop at year 2030 for INECP scenario and in 2050 for long-term scenarios. *Electrical steel contains CRM additives: silicon (in addition to iron); **Magnets contain CRM: Boron, Dysprosium, Neodymium, Praseodymium.

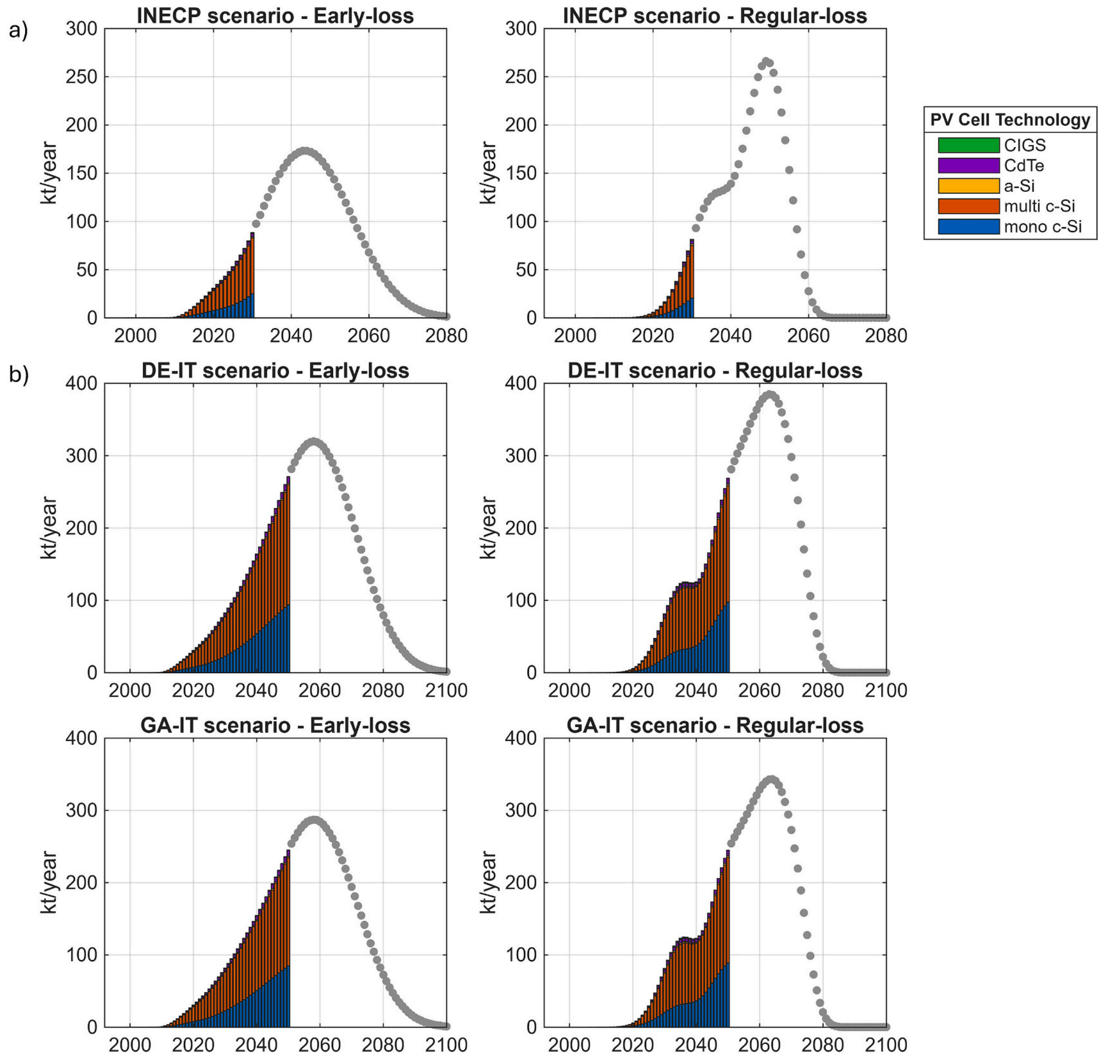

Fig. 5. Projected waste from photovoltaic (PV) panels in Italy, highlighting PV cells technologies, for a) short-term scenario (INECP) and b) long-term scenarios (DE-IT and GA-IT) and both early-loss and regular-loss lifetime profiles. Installations are assumed to stop at year 2030 for INECP scenario and in 2050 for long-term scenarios.

silicon (4–5 kt y^{-1} by 2030 and 9–10 kt y^{-1} by 2050) and copper (700–800 t y^{-1} by 2030 and 2–3 kt y^{-1} by 2050).

3.4. Wind turbine blades

The amount of WTBs waste in 2030 is projected to be around 8.2 kt $year^{-1}$ in all the analysed scenarios (Fig. 7). The waste generated by the installations up to the targets of INECP peaks in 2045 (17.2 kt $year^{-1}$). Blade waste coming from offshore deployments are found only from 2047. In 2050, the model forecasts around 15.6 kt $year^{-1}$ of waste under DE-IT scenario and about 13.3 kt $year^{-1}$ under GA-IT scenario. However, from 2050 onwards, the EoL blades coming from offshore installations are sharply increasing, determining a peak of waste generation after 2070 for both scenarios.

In terms of recoverable materials (Fig. 8, Table S17), the most relevant contributions are given by the reinforcing glass fibres and the resins. In 2030, the GFRP (as sum of GF and resins) is around 7 kt $year^{-1}$ in all scenarios. In 2050, instead, the GFRP amount ranges between 11.3 kt $year^{-1}$ and 13.3 kt $year^{-1}$. According to the composition by Li et al. (2022), WTBs can contain small amounts of CRMs in their metallic components, primarily copper and aluminium, accounting for approximately 0.44% of metal parts. Based on this, recoverable CRM quantities are projected at approximately 1 t $year^{-1}$ by 2030 and 2 t $year^{-1}$ by 2050. For WTs, additional CRM content is present as alloying elements in steel components and in generators that rely on permanent magnets but are outside the scope of this analysis.

4. Discussion

Comparisons of results across scenarios (Table S19) are limited to their overlapping time horizons: results beyond the temporal scope of the scenario, i.e. beyond 2030 for INECP, are not considered meaningful. Therefore, common years, particularly 2030, are used to illustrate how different deployment trajectories influence the timing and magnitude of waste generation. Within this framework, the DE-IT scenario shows the highest annual waste flows, reflecting the full-scale transition to electric mobility and stationary storage, driven by deep electrification depicted by this scenario. However, by looking at the results every 5 years, the INECP scenario exhibits a more rapid surge in waste generation compared to DE-IT and GA-IT, resulting in higher values in 2030, due to the more ambitious short-term targets, compared to the more gradual ones for 2040. The decrease of the waste curves is solely due to the cut-off of model inputs in 2030 and 2050. If the annual input data were not truncated to the targets but instead continued to grow or level off, the waste curves would similarly display continuous growth or levelling off, reflecting the dynamic nature of input–output flows. The tail ends of the

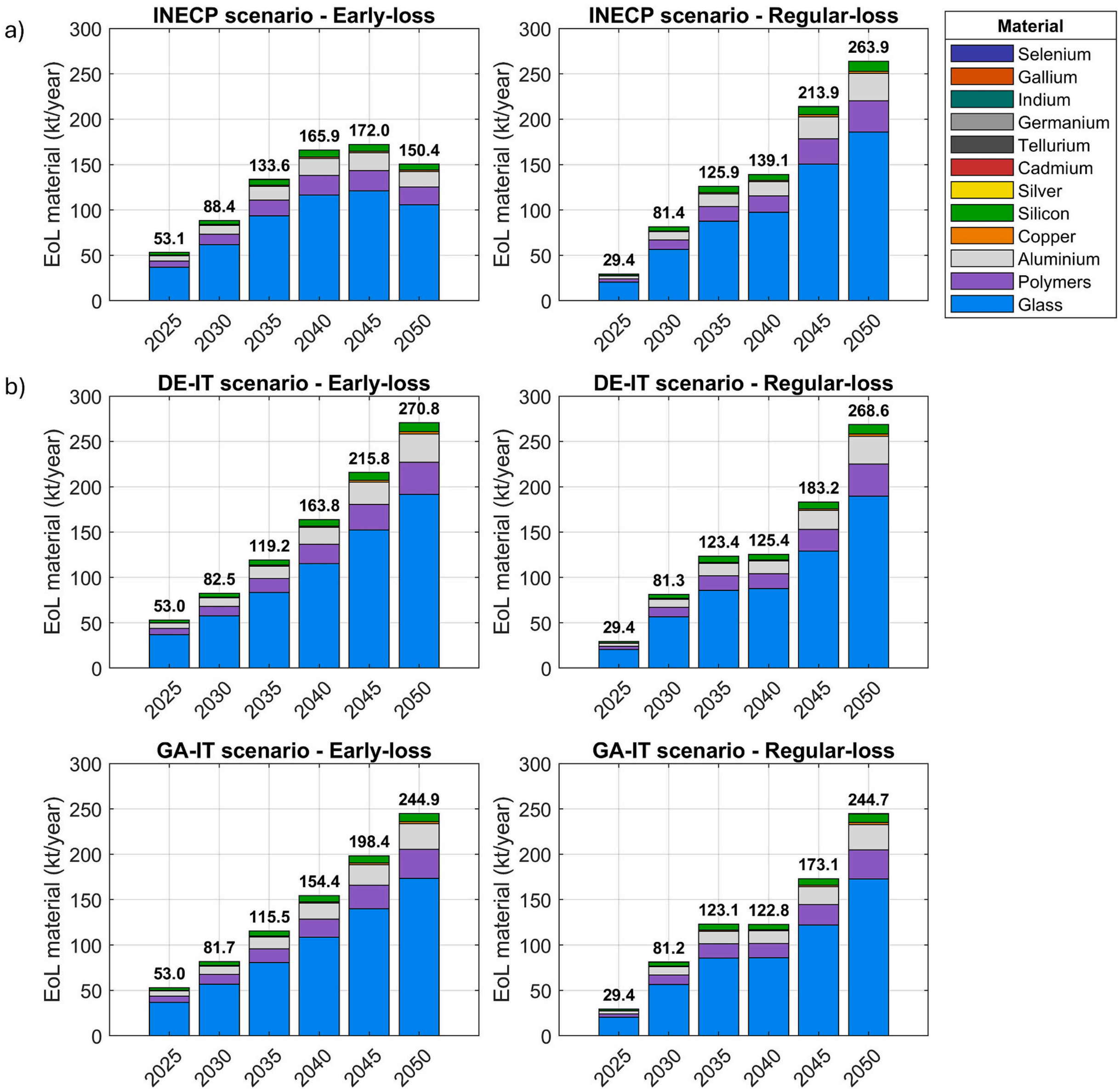

Fig. 6. Estimated materials and elements in EoL PV panels in Italy for the 3 analysed scenarios: a) short-term (INECP) and b) long-term (DE-IT and GA-IT), under two lifetime profiles (early-loss and regular-loss). Note that for INECP scenario, installations are assumed to stop at 2030 targets and for DE-IT and GA-IT in 2050.

Weibull curves prove how the installations up to year 2030 or 2050 affect future waste generation far beyond the time they are deployed/ put on market.

A comparison with existing national studies further supports the robustness of the results. Motus-E (2023) estimates 367 kt year^{-1} of EoL EV batteries by 2050 in Italy, which is consistent with values obtained in this study for the GA-IT scenario (412 kt year^{-1} from BEVs and 23 kt year^{-1} from PHEVs).

Similarly, Corrias et al. (2021) estimates a total of 1,604,981 tonnes of PV panels to be decommissioned in Italy over the decade 2031–2040, a figure that aligns with 1,246,400 tonnes projected here under the DE-IT early-loss scenario. Differences can be attributed to variations in assumed lifetimes, deployment trajectories and modelling approaches, but the overall agreement strengthens confidence in the order of magnitude of the projected waste flows.

Existing European-level estimates of WTBs waste either do not report country-specific results (Sommer et al., 2020) or indicate that Italy is not expected to be a hotspot for this waste stream within the analysed time horizon (Lichtenegger et al., 2020), which is consistent with the projections showing that quantities are expected to steeply increase only after 2050.

4.1. CRMS content in waste

The present analysis estimates the potentially recoverable materials from EoL streams based on their composition and projected waste flows, representing a theoretical material availability rather than the actual quantities effectively recycled. Recycling process efficiencies and the quality of recycled materials suitable for different secondary applications were not considered, due to the high variability among available recycling technologies and the additional uncertainty these considerations would introduce. A comprehensive assessment of current recycling processes, performances and challenges related to achieving high-quality secondary materials is provided by Grosso and Rigamonti (2025). The future evolution of battery chemistries, which was modelled in this study, indicates an increasing market share for LFP and LMFP batteries in the upcoming years. LFP and LMFP have the advantage of lower CRM requirements (especially cobalt), compared to NMC, and

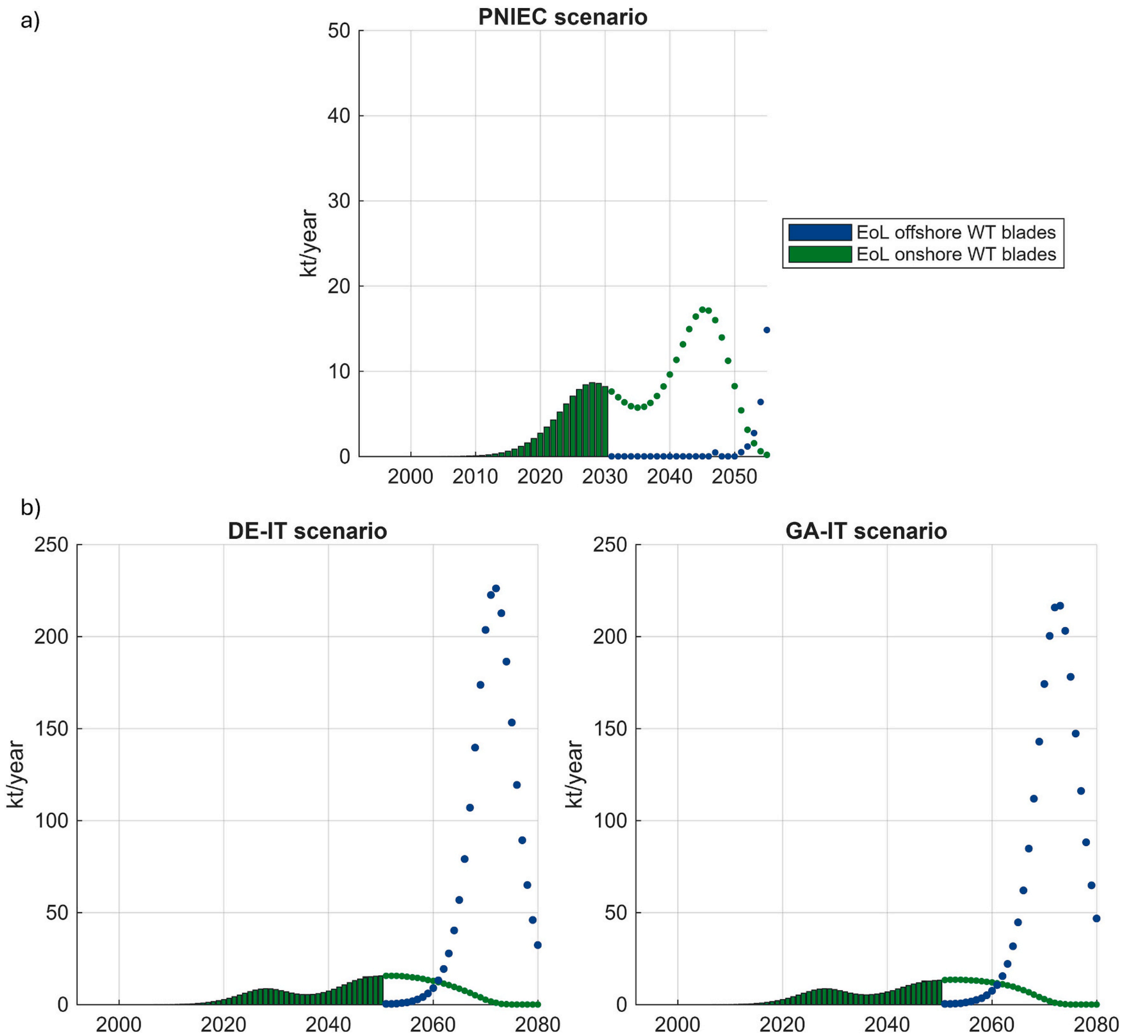

Fig. 7. Predicted wind turbine blades waste, in Italy, following a) short-term (INECP) scenario and b) long-term scenario (DE-IT and GA-IT). Installations are assumed to stop at year 2030 for INECP scenario and in 2050 for long-term scenarios.

production costs but, on the other hand, this poses a trade-off in terms of a lower recycling value (TNO innovation for life, 2025).

Regarding PV panels waste projections, glass is the most relevant material; although other materials appear negligible in terms of mass, they can be important due to their criticality, like gallium or germanium, or economic value, such as silver (Graulich et al., 2021). Materials present in smaller quantities, such as silicon, silver and copper, account for nearly 70% of the economic value of PV modules treated (Salas-Redondo et al., 2024). Given this composition, particular attention should be paid to CRMs, including aluminium, copper, silicon, germanium and gallium.

The quantification of CRMs in the waste flows of electric motors and WTBs is particularly challenging. This difficulty arises because several materials are composite in nature, and certain metals incorporate CRMs, such as the rare-earth elements contained in permanent magnets and copper and aluminium in metallic components of WTBs. These heterogeneous material formulations are difficult to quantify accurately, especially given the limited availability of detailed compositional data.

4.2. Limitations and recommendations

This study presents a systematic and replicable framework to forecast future waste streams using historical data and scenario-based projections, providing the first comprehensive assessment for Italy. However, as with any long-term forecast analysis, it has some limitations. One is the reliance on average technical parameters available at the global or European scale and limited information on the Italian context. For example, missing decommissioning records and lack of systematic monitoring of retired assets hinder the definition of country-specific lifetime profiles and Weibull parameters. Moreover, future trends are hardly predictable as they can be heavily influenced by market, regulatory or technological changes.

Additional uncertainty could have been introduced by the choice not to account for the replacement of stock reaching EoL, when modelling the future inflows. To assess the relevance of this assumption, an additional calculation including replacement-driven inflows, estimated through a first-pass application of the lifetime distribution, was performed (Fig. S6). The results show that this omission has a negligible effect on the projected EoL flows over the analysed period.

Additional technology-specific uncertainties include assumptions about fixed battery capacities, energy densities, and material composition for Li-ion batteries (although the temporal evolution of battery chemistries is accounted for, as illustrated in Fig. S2), or average mass for electric motors. Future developments in battery technology, particularly the expected increase in energy density, should be considered in further analyses, as higher energy density would lead to lighter battery packs and consequently lower waste generation for a given capacity. Thus, the results of the current study are cautious. For PV panels, market-share evolution and design parameters can be uncertain. Also, WTBs mass and material composition show high variability across

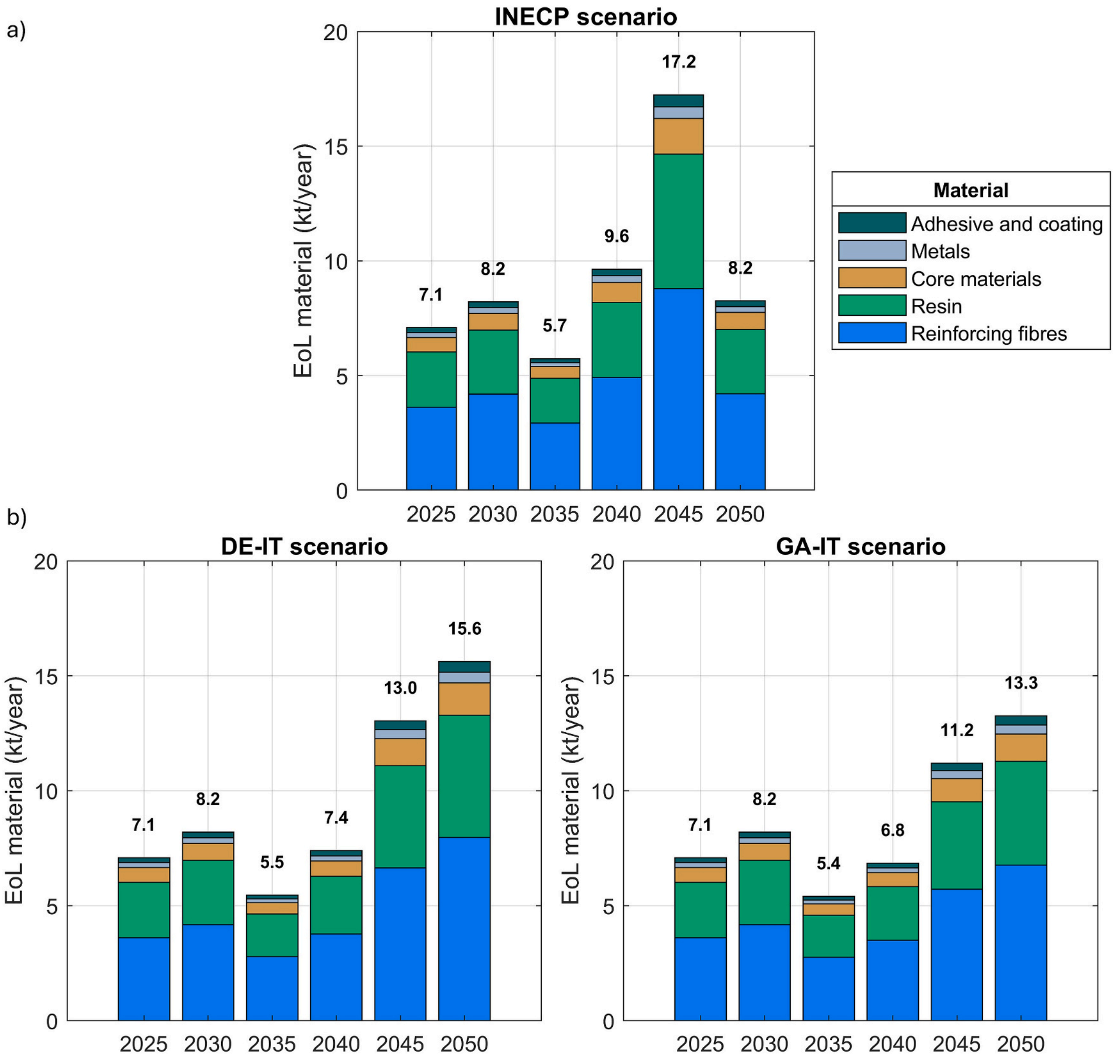

Fig. 8. Projections on materials in wind turbine blades waste, in Italy, in the 3 analysed scenarios: for a) short-term (INECP) and b) long-term (DE-IT and GA-IT). Note that for INECP scenario installations are assumed to stop at 2030 targets and for DE-IT and GA-IT in 2050.

power ratings and manufacturers. The lack of national official data on existing and decommissioned WTs, unlike other European countries (Kramer et al., 2024), and of the maintenance-related waste prevent more accurate predictions.

Systematic information on specific end-of-life practices (such as reuse, refurbishment) and repowering remains limited, and their influence on waste estimates could not be captured.

These limitations point to several priority areas where policy intervention and improved data collection could significantly enhance future assessments. First, the introduction of more granular and technology-specific waste codes, such as those recently proposed at the EU level for batteries (Directorate-General for Environment, 2025), would substantially improve traceability and data quality across the waste management chain. Similar efforts could be extended to PV modules, electric motors and composite materials from WTBs, which are still grouped under generic waste categories. PVs are, in fact, classified under WEEE (e.g. codes 160214 and 200136) (European Commission, 2025; Graulich et al., 2021), and wind turbine blades as construction and demolition plastic waste, hindering accurate quantification and the development of dedicated recycling infrastructure. In the case of electric motors, the absence of dedicated waste codes and sector-specific recycling requirements similarly limits the recovery of high-value materials, reinforcing a focus only on bulk metal recovery (Li et al., 2024).

Second, regulatory frameworks could be strengthened by complementing existing recycling-efficiency targets with technology-specific collection ones. For instance, the EU Battery Regulation (European Parliament and Council, 2023) strengthens producer responsibility and sets ambitious targets for recycling efficiency (70% for Li-ion batteries by 2030) and CRMs recovery (95% for cobalt and copper, 80% for lithium, and 95% for nickel), but the absence of collection-rate targets specific to EV batteries may limit the effectiveness of these measures in practice.

Regarding PV panels, the EU WEEE Directive covers PVs and sets the collection (85%), recovery (85%) and reuse/recycling (80%) targets. In practice, the collection target is widely viewed as unrealistic due to the long lifetimes and the market volatility of PV panels (Graulich et al., 2021). Moreover, it lacks CRM-specific recycling targets: its minimum recovery/recycling thresholds can be met by recovering only bulk materials, offering little incentive to extract valuable materials such as silver and silicon.

5. Conclusions

The estimation of future waste streams from key energy-transition technologies, i.e. lithium-ion batteries, electric motors, photovoltaic panels and wind turbine blades, is essential for strategic planning, as these rapidly growing and material-intensive flows will require dedicated end-of-life management infrastructure and, at the same time, represent a growing secondary resource base whose proper treatment and recycling can contribute to the recovery of critical raw materials and partially offset future primary demand.

Using a dynamic material flow model aligned with Italy's national energy targets for climate neutrality, this study projects EoL quantities up to 2050, revealing steep increases across all technologies. Li-ion batteries from EVs and BESSs reach maximum estimates of around 32 kt year^{-1} by 2030 and up to 736 kt year^{-1} by 2050 in the most ambitious electrification scenario. Photovoltaic waste is also projected to grow significantly, reaching up to 88 kt year^{-1} by 2030 and 271 kt year^{-1} by 2050. Electric motors from waste EVs increase from 6 kt year^{-1} to around 86 kt year^{-1} by 2050. Wind blades waste rises from 8 kt year^{-1} to approximately 16 kt year^{-1}; however, the amounts are projected to surge from 2050 onwards, due to decommissioning of offshore deployments.

The approach used for the analysis is fully replicable, since it is accompanied by all methodological specifications, modelling assumptions, and data structures required to implement the forecasting framework in any country or region.

These results support planning of collection and recycling infrastructure and highlight regulatory gaps limiting high-quality recycling. Policy priorities include dedicated waste codes in the European List of Wastes, collection and recovery targets, and investment in treatment capacity and advanced recovery technologies to turn emerging waste streams into secondary resources.

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7. Declaration of AI-assisted technologies in the manuscript preparation process

During the preparation of this work the authors used ChatGPT Plus to assist in developing the MATLAB code for the predictive model. After using this tool, the author reviewed and edited the content as needed and take full responsibility for the content of the published article.

CRediT authorship contribution statement

Federica Dei: Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Gaia Brussa:** Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Stefano Puricelli:** Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Lucia Rigamonti:** Writing – review & editing, Supervision, Project administration, Funding acquisition, Conceptualization. **Mario Grosso:** Writing – review & editing, Supervision, Project administration, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.wasman.2026.115483.

Data availability

Data will be made available on request.

References

Abrahamsen, B.A., Beauson, J., Wilhelm Lund, K., Skov Madsen, E., Philipp Rudolph, D., Pagh Jensen, J., 2024. Method for estimating the future annual mass of decommissioned wind turbine blade material in Denmark. Wind Energy 27 (2), 165–178. https://doi.org/10.1002/we.2882.

Ambarwati, L., Ardi, R., Komarudin, 2024. Developing conceptual model for estimating waste volume of retired electric vehicle battery. IEEE International Conference on Industrial Engineering and Engineering Management (IEEM) 2024, 1069–1073. https://doi.org/10.1109/IEEM62345.2024.10857149.

ETIPWind. *How wind is going circular - blade recycling*, 2019. https://etipwind.eu/files/reports/ETIPWind-How-wind-is-going-circular-blade-recycling.pdf.

Aeroporti di Roma. (n.d.). *PIONEER: sostenibilità aeroportuale sullo stoccaggio di batterie di seconda mano* . https://www.adr.it/progetto-pioneer.

Argonne National Laboratory (ANL). (2024). *R&D GREET Battery Module*. https://greet.anl.gov/greet_battery.

Carrara, S. (2020). Raw materials demand for wind and solar PV technologies in the transition towards a decarbonised energy system. https://data.europa.eu/doi/10.2760/160859.

Corrias, P., Ciorba, U., Felici, B. (2021). *Il fine vita del fotovoltaico in Italia implicazioni socio-economiche ed ambientali* . https://www.pubblicazioni.enea.it/le-pubblicazioni-enea/edizioni-enea/anno-2021/il-fine-vita-del-fotovoltaico-in-italia-implicazioni-socio-economiche-ed-ambientali.html.

de l'Epine, M., Kaizuka, I. (2024). Trends in Photovoltaic Applications 2024. doi: 10.69766/JNEW6916.

Directorate-General for Environment. (2025). *New battery-related waste codes will boost circular management of batteries and their critical raw materials*. https://environment.ec.europa.eu/news/battery-related-waste-codes-update-set-boost-circular-economy-2025-03-05_en.

Drabik, E., & Rizos, V. (2018). *Prospects for electric vehicle batteries in a circular economy*. https://circulareconomy.europa.eu/platform/sites/default/files/circular_economy_impacts_batteries_for_evs.pdf.

European Commission. (2017). EU 2017/699. https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:32017R0699.

European Commission: Joint Research Centre. (2025). *Circular economy strategies for the EU's renewable electricity supply*. Publications Office of the European Union. doi: doi/10.2760/5598339.

European Parliament and Council. (2023). *Regulation (EU) 2023/1542*. https://eur-lex.europa.eu/eli/reg/2023/1542/oj.

Eurostat. (2025). *Waste electrical and electronic equipment (WEEE) by waste management operations - open scope, 6 product categories (from 2018 onwards)*. https://ec.europa.eu/eurostat/databrowser/view/env_waseleeos__custom_19357180/default/table.

Bruno, M., Fiore, S., 2023. Material flow analysis of lithium-ion battery recycling in europe: environmental and economic implications. Batteries 9 (4), 231. https://doi.org/10.3390/batteries9040231.

Evro, S., Ajumobi, A., Mayon, D., Tomomewo, O.S., 2024. Navigating battery choices: a comparative study of lithium iron phosphate and nickel manganese cobalt battery technologies. Future Batteries 4, 100007. https://doi.org/10.1016/j.fub.2024.100007.

Fluchs, S., 2020. The diffusion of electric mobility in the European Union and beyond. Transp. Res. Part D: Transp. Environ. 86, 102462. https://doi.org/10.1016/j.trd.2020.102462.

Fonte, R., Xydis, G., 2021. Wind turbine blade recycling: an evaluation of the European market potential for recycled composite materials. J. Environ. Manage. 287. https://doi.org/10.1016/j.jenvman.2021.112269.

Franzoni, A., Leggerini, C., Bannò, M., 2024. A predictive framework for photovoltaic waste quantities and recovery values: insights and application to the italian context. Environ. Clim. Technol. 28 (1), 243–257. https://doi.org/10.2478/rtuect-2024-0020.

Fraunhofer and PSE Projects GmbH. (2024). *Photovoltaic report*. https://www.ise.fraunhofer.de/en/publications/studies/photovoltaics-report.html.

Garrison, W.M., 2001. Steels: classifications. Encyclopedia of Materials: Science and Technology 8840–8843. https://doi.org/10.1016/B0-08-043152-6/01587-4.

Gestore dei Servizi Energetici S.p.A. (2025). *Rapporto statistico solare fotovoltaico 2024*. https://www.gse.it/documenti_site/Documenti%20GSE/Rapporti%20statistici/Solare%20Fotovoltaico%20-%20Rapporto%20Statistico%202024.pdf.

Graulich, K., Bulach, W., Betz, J., & Dolega, P. (2021). *Emerging waste streams – Challenges and opportunities*. https://www.oeko.de/publikation/emerging-waste-streams-challenges-and-opportunities/.

Grosso, M., Rigamonti, L. (Eds.), 2025. Waste Flows Generated by the Energy Transition. Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-88951-6.

GWEC. (2021). *Italy Offshore Wind Technical Potential*. https://marketintelligence.gwec.net/wp-content/uploads/2021/06/Italy_Offshore-Wind-Technical-Potential_GWEC-OREAC.pdf.

Huster, S., Glöser-Chahoud, S., Rosenberg, S., Schultmann, F., 2022. A simulation model for assessing the potential of remanufacturing electric vehicle batteries as spare parts. J. Clean. Prod. 363, 132225. https://doi.org/10.1016/j.jclepro.2022.132225.

IDTechEx. (2024). *Electric Motors for Electric Vehicles 2025-2035: Technologies, Materials, Markets, and Forecasts*. https://www.idtechex.com/tw/research-report/electric-motors/1031.

IEA. (2016). *Photovoltaic Power Systems Programme Annual Report*. https://iea-pvps.org/wp-content/uploads/2020/01/IEA-PVPS_RA2016-web.pdf.
IEA. (2021). *The Role of Critical Minerals in Clean Energy Transitions*. https://www.iea.org/reports/the-role-of-critical-minerals-in-clean-energy-transitions.
IEA. (2023). Net Zero Roadmap: A Global Pathway to Keep the 1.5 °C Goal in Reach. https://www.iea.org/reports/net-zero-roadmap-a-global-pathway-to-keep-the-15-c-goal-in-reach.
IEA. (2024). *Global EV Outlook 2024*. https://www.iea.org/reports/global-ev-outlook-2024.
IEA PVPS. (2020). *Life Cycle Inventories and Life Cycle Assessments of Photovoltaic Systems* . https://iea-pvps.org/wp-content/uploads/2020/12/IEA-PVPS-LCI-report-2020.pdf.
IRENA. (2024). *Critical materials: Batteries for electric vehicles*. https://www.irena.org/-/media/Files/IRENA/Agency/Publication/2024/Sep/IRENA_Critical_materials_Batteries_for_EVs_2024.pdf.
Johst, P., Bühl, M., Enderle, C., Kupfer, R., Modler, N., Böhm, R., 2024. Forecasting wind turbine blade waste with material composition and geographical distribution: methodology and application to Germany. Resour. Conserv. Recycl. 211. https://doi.org/10.1016/j.resconrec.2024.107876.
Koshta, N., Patra, S., Singh, S.P., 2021. Estimation of E-waste at micro level for reverse logistics: a case of Delhi. J. Clean. Prod. 314, 128063. https://doi.org/10.1016/j.jclepro.2021.128063.
Kramer, K.J., Abrahamsen, A.B., Beauson, J., Hansen, U.E., Clausen, N.E., Velenturf, A.P.M., Schmidt, M., 2024. Quantifying circular economy pathways of decommissioned onshore wind turbines: the case of Denmark and Germany. Sustainable Prod. Consumption 49, 179–192. https://doi.org/10.1016/j.spc.2024.06.022.
Lahuerta, F., Gesto, D., Prieto, C., Johst, P., Kucher, M., Mozas, E., Gracia, O., Böhm, R., Bielsa, J.M., 2023. Decommissioning inventory for wind turbine blades installed until 2022 in europe. ICCM International Conferences on Composite Materials. https://doi.org/10.1007/s42824-023-00084-8.
Lefeuvre, A., Garnier, S., Jacquemin, L., Pillain, B., Sonnemann, G., 2019. Anticipating in-use stocks of carbon fibre reinforced polymers and related waste generated by the wind power sector until 2050. Resour. Conserv. Recycl. 141, 30–39. https://doi.org/10.1016/j.resconrec.2018.10.008.
Li, C., Mogollón, J.M., Tukker, A., Dong, J., von Terzi, D., Zhang, C., Steubing, B., 2022. Future material requirements for global sustainable offshore wind energy development. Renew. Sustain. Energy Rev. 164, 112603. https://doi.org/10.1016/J.RSER.2022.112603.
Li, Z., Hamidi, A.S., Yan, Z., Sattar, A., Hazra, S., Soulard, J., Guest, C., Ahmed, S.H., Tailor, F., 2024. A circular economy approach for recycling Electric Motors in the end-of-life Vehicles: a literature review. Resour. Conserv. Recycl. 205, 107582. https://doi.org/10.1016/j.resconrec.2024.107582.
Lichtenegger, G., Rentizelas, A.A., Trivyza, N., Siegl, S., 2020. Offshore and onshore wind turbine blade waste material forecast at a regional level in Europe until 2050. Waste Manag. 106, 120–131. https://doi.org/10.1016/j.wasman.2020.03.018.
Liu, P., Barlow, C.Y., 2017. Wind turbine blade waste in 2050. Waste Manag. 62, 229–240. https://doi.org/10.1016/j.wasman.2017.02.007.
Mahmoudi, S., Huda, N., Behnia, M., 2019. Photovoltaic waste assessment: forecasting and screening of emerging waste in Australia. Resour. Conserv. Recycl. 146, 192–205. https://doi.org/10.1016/j.resconrec.2019.03.039.
Maisel, F., Neef, C., Marscheider-Weidemann, F., Nissen, N.F., 2023. A forecast on future raw material demand and recycling potential of lithium-ion batteries in electric vehicles. Resour. Conserv. Recycl. 192, 106920. https://doi.org/10.1016/j.resconrec.2023.106920.
Marchetti, C., 1983. The automobile in a system context. Technol. Forecast. Soc. Chang. 23 (1), 3–23. https://doi.org/10.1016/0040-1625(83)90068-9.
Ministero dell'Ambiente e della Sicurezza Energetica. (2024). *Piano Nazionale Integrato per l'Energia e il Clima (PNIEC)*. https://www.mase.gov.it/portale/documents/d/guest/pniec_2024_revfin_01072024-pdf.
Ministero dell'Ambiente e della Tutela del Territorio e del Mare, Ministero dello Sviluppo Economico, Ministero delle Infrastrutture e dei Trasporti, & Ministero delle Politiche agricole, A. e F. (2021). *Strategia Italiana di lungo termine sulla riduzione delle emissioni dei gas a effetto serra*. https://www.mase.gov.it/portale/documents/d/guest/nlts_lts_gennaio_2021-pdf.
Motus-E. (2023). *Il riciclo delle batterie dei veicoli elettrici @2050: scenari evolutivi e tecnologie abilitanti*. https://www.motus-e.org/wp-content/uploads/2023/03/Motus-E_PwCS_PoliMi_Il-riciclo-delle-batterie-dei-veicoli-elettrici-@2050-scenari-evolutivi-e-tecnologie-abilitanti.pdf.
Monier, V., Hestin, M. (2011). *Study on Photovoltaic Panels Supplementing the Impact Assessment for a Recast of the WEEE Directive*. https://ec.europa.eu/environment/pdf/waste/weee/Study%20on%20PVs%20Bio%20final.pdf.
Nabi, A.A., Nema, A.K., 2024. An in-depth analysis of factors and forecasting techniques for emerging solid waste streams. J. Environ. Manage. 367, 122037. https://doi.org/10.1016/j.jenvman.2024.122037.
Paiano, A., 2015. Photovoltaic waste assessment in Italy. Renew. Sustain. Energy Rev. 41, 99–112. https://doi.org/10.1016/j.rser.2014.07.208.
Rettenmeier, M., Petrik, D., Möller, M., Sauer, A., 2025. A modeling framework and benchmark for end-of-life automotive traction battery pack forecasting. J. Clean. Prod. 491, 144752. https://doi.org/10.1016/j.jclepro.2025.144752.
Rietmann, N., Hügler, B., Lieven, T., 2020. Forecasting the trajectory of electric vehicle sales and the consequences for worldwide CO2 emissions. J. Clean. Prod. 261, 121038. https://doi.org/10.1016/j.jclepro.2020.121038.
Rogers, E.M., 1962. Diffusion of Innovations Vol. 12. Collier-Macmillan.
Ruoso, A.C., Ribeiro, J.L.D., 2022. The influence of countries' socioeconomic characteristics on the adoption of electric vehicle. Energy Sustain. Dev. 71, 251–262. https://doi.org/10.1016/j.esd.2022.10.003.
Salas-Redondo, C., Bade, S., Chalaux, A., Luo, Y., 2024. Recycled Silicon for Chlorosilane production. SSRN Electron. J. https://doi.org/10.2139/ssrn.4943277.
Sanclemente Crespo, M., Van Ginkel González, M., Talens Peiró, L., 2022. Prospects on end of life electric vehicle batteries through 2050 in Catalonia. Resour. Conserv. Recycl. 180, 106133. https://doi.org/10.1016/j.resconrec.2021.106133.
Shafique, M., Akbar, A., Rafiq, M., Azam, A., Luo, X., 2023. Global material flow analysis of end-of-life of lithium nickel manganese cobalt oxide batteries from battery electric vehicles. Waste Management & Research: the Journal for a Sustainable Circular Economy 41 (2), 376–388. https://doi.org/10.1177/0734242X221127175.
Shafique, M., Rafiq, M., Azam, A., Luo, X., 2022. Material flow analysis for end-of-life lithium-ion batteries from battery electric vehicles in the USA and China. Resour. Conserv. Recycl. 178, 106061. https://doi.org/10.1016/j.resconrec.2021.106061.
Sharma, A., Mahajan, P., Garg, R., 2024. End-of-life solar photovoltaic panel waste management in India: forecasting and environmental impact assessment. Int. J. Environ. Sci. Technol. 21 (2), 1961–1980. https://doi.org/10.1007/s13762-023-04953-2.
Sommer, V., Stockschläder, J., Walther, G., 2020. Estimation of glass and carbon fiber reinforced plastic waste from end-of-life rotor blades of wind power plants within the European Union. Waste Manag. 115, 83–94. https://doi.org/10.1016/J.WASMAN.2020.06.043.
Tan, Q., Li, J., 2014. A study of waste fluorescent lamp generation in mainland China. J. Clean. Prod. 81, 227–233. https://doi.org/10.1016/j.jclepro.2014.06.048.
Tankou, A., Bieker, G., Hall, D.. *Scaling up reuse and recycling of electric vehicle batteries: assessing challenges and policy approaches*. https://theicct.org/publication/recycling-electric-vehicle-batteries-feb-23/.
Tazi, N., Orefice, M., Marmy, C., Baron, Y., Ljunggren, M., Wäger, P., Mathieux, F., 2023. *Initial analysis of selected measures to improve the circularity of critical raw materials and other materials in passenger cars*. Publications Office of the European Union. https://doi.org/10.2760/207541.
Terna. (2023). *Studio sulle tecnologie di riferimento per lo stoccaggio di energia elettrica*. https://download.terna.it/terna/Studio_tecnologie_di_accumulo_8db9511fbdd7601.pdf.
Terna. (2024). *Documento di Descrizione degli Scenari*. https://download.terna.it/terna/Documento_Descrizione_Scenari_2024_8dce2430d44d101.pdf.
TheWindPower. (2024). *Italy wind farms database*. https://www.thewindpower.net/store_country_en.php?id_zone=7.
UNRAE. (2025). *L'auto 2024 Sintesi Statistica*. https://www.unrae.it/files/AnnualReportUNRAE_2024_68628e8314caf.pdf.
TNO innovation for life. *Economically viable recycling process for inexpensive raw materials*. https://www.tno.nl/en/newsroom/2025/01/recovering-raw-materials-batteries/.
Transport, Environment.. *From waste to value: Europe's opportunity for self-sufficiency and a low-impact supply chain*. https://www.transportenvironment.org/articles/from-waste-to-value-the-potential-for-battery-recycling-in-europe.
Volan, T., Vaz, C.R., Uriona-Maldonado, M., 2021. Scenarios for end-of-life (EOL) electric vehicle batteries in China. Revista De Gestão 28 (4), 335–357. https://doi.org/10.1108/REGE-12-2020-0143.
wind-turbine-models.com. (2025). *wind-turbine-models.com*. https://en.wind-turbine-models.com/turbines.
Winjobi O., Dai, Q., & Kelly, J. C. (2020). *Update of Bill-of-Materials and Cathode Chemistry addition for Lithium-ion Batteries in GREET® 2020*. https://greet.anl.gov/files/bom_lib_2020.
Wu, Y., Yang, L., Tian, X., Li, Y., Zuo, T., 2020. Temporal and spatial analysis for end-of-life power batteries from electric vehicles in China. Resour. Conserv. Recycl. 155, 104651. https://doi.org/10.1016/j.resconrec.2019.104651.
Zhao, J. (2023). *Mitsui & Co. Global Strategic Studies Institute Monthly Report*. https://www.mitsui.com/mgssi/en/report/detail/__icsFiles/afieldfile/2023/09/19/2308t_zhao_e.pdf.