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Raw Material Gaps on the way to Net Zero by 2050? A case study for Nd focusing on wind energy and EVs

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Affidavit

I, **OLIVIER KARL ANTON HELDWEIN, MSC**, hereby declare

1. that I am the sole author of the present Master's Thesis, "RAW MATERIAL GAPS ON THE WAY TO NET ZERO BY 2050? A CASE STUDY FOR ND FOCUSING ON WIND ENERGY AND EVS", 109 pages, bound, and that I have not used any source or tool other than those referenced or any other illicit aid or tool, and
2. that I have not prior to this date submitted the topic of this Master's Thesis or parts of it in any form for assessment as an examination paper, either in Austria or abroad.

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Abstract

In order to limit the adverse impacts of climate change we already feel today, humanity has to stop adding greenhouse gases to the atmosphere. Many countries have committed to do that and pledged to reach net zero by the mid-century. To support these countries, the International Energy Agency has published a landmark report outlining a technically feasible and economically viable roadmap to reach net zero globally by 2050. This study dynamically modelled the demand for Nd, a critical raw material used in wind turbines and electric vehicles, that is needed to implement the roadmap outlined by the International Energy Agency and explores different scenarios for Nd demand. The results show that mining has to increase to meet the demand for Nd for wind turbines and EVs. Recycling will partly offset the demand for primary Nd from 2035 on and could cover 50 – 68 % of the Nd demand for wind turbines and 32 – 60 % for EVs in 2050. Assuming an increase in mining production of ~10% annually, the demand for primary Nd for wind turbines and EVs alone could exceed production for a short period of time around 2030 under a high demand scenario. If other uses for Nd are considered too, the high demand scenario overshoots the supply and only from 2035 onwards the demand can be met if Nd is recycled efficiently (recycling rate >50%). A considerable supply risk for Nd arises from the fact, that illegal mining in China makes up around 30% of the total supply. However, for the low demand scenario official mining, without any illegal mining, would be able cover all the demand and mining would not have to increase from 2030 onwards, as all increase in demand could be covered by recycling.

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List of Abbreviations

BEV	battery electric vehicle
DD	direct-drive
DFIG	doubly-fed induction generator
EESG	electrically excited synchronous generator
EOL	end-of-life
EV	electric vehicle
FCEV	fuel-cell electric vehicle
GB	gearbox
HEV	hybrid electric vehicle
HTS	high-temperature superconductor
ICE	internal combustion engine [vehicle]
PHEV	plug-in hybrid electric vehicle
PMSG	permanent magnet synchronous generator
REE	rare earth element
REO	rare earth oxide
SCIG	squirrel-cage induction generator

Content

1. Introduction

The introduction presents the motivation of the study and gives the reader the necessary background to understand the core part of the study and follow the methods and results.

1.1 Motivation

Global warming and the associated ecological and social changes are the most important challenges of humanity of our time and they require a global answer. Rapid decarbonization and ensuring reliable access to clean energy for all are at the heart of securing sustainable development and preventing a collapse of ecological, social, and economic systems. With its flagship report "Net Zero by 2050 – A Roadmap for the Global Energy Sector" (Roadmap to Net Zero; Net Zero 2050 Report) the international energy agency (IEA) laid out a technically feasible, cost-effective and socially acceptable pathway to reach net-zero emissions globally (IEA 2021c). The report shows clearly that the goal of reaching net zero globally is achievable but challenging and requires immediate determined action. One of the big challenges of the green transition from a fossil fuel based economy to a renewable energy based economy is the raw material need of green technologies (IEA 2021b). For many of the transition metals, rare-earth elements and other raw materials ranging from lithium to natural rubber, supply risk is high due to politically unstable conditions in the producing countries, concentration of the world production in very few countries and geopolitical tensions between major economic blocks, or simply because demand projections are higher than supply prospects (e.g. Bobba et al., 2020).

The aim of this study, is to take a closer look at one key raw material required in the energy transition for renewable energy and decarbonising transport, assess the raw material need of the IEA Roadmap to Net Zero and find out whether the demand can be met based on mining and recycling prospects. Neodymium (Nd) was chosen for this in-depth analysis as this rare earth element is a crucial component in strong permanent magnets (NdFeB magnets) which are commonly used in wind turbines and electric vehicle (EV) motors, two key technologies to decarbonize energy generation and transport.

Previous studies have already modeled the Nd demand for wind energy and EVs or both under different scenarios and for different regions. For example, Elshkaki and Graedel (2013) modeled the global metal flows and stocks for electricity generation tehchnologies, Li et al. (2020) and Deng et al. (2020) modeled the global metal demand for wind energy, Habib and Wenzel (2016) did the same for a particular type of wind turbines, Månberger and Stenqvist (2018) modeled metal demands for the renewable energy transition including wind energy and EVs, and Deetman et al. (2018) not only assessed the global Nd demand for EVs and wind turbines but also for household appliances. Several studies only focus on one country or region, for example Fishman et al. (2018), examine the rare earth demand for EVs in the US, Viebahn et al. (2015) the Nd-demand for wind turbines in Germany, and Yao et al. (2021) and Sekine et al. (2017) performed dynamic material analyses of Nd in China and Japan, respectively. The Joint Research Council of the EU has published multiple reports assessing the supply and demand of critical raw materials (including Nd) in energy generation, EVs and other strategic technologies and sectors (European Commission n.d.). Also international organisations such as the World Bank and the International Energy Agency published reports dedicated to the demand for metals or minerals for the energy transition (World Bank 2017; 2020; IEA 2021b). This study assesses for the first time the global Nd demand to implement the Roadmap to Net Zero by 2050 of the IEA, which is a technically feasible, cost-effective and socially acceptable scenario and can serve as a guideline for the countries having pledged to reach net zero by 2050.

1.2 Net Zero by 2050 – A Roadmap for the Global Energy Sector

The flagship report "Net Zero by 2050 – A Roadmap for the Global Energy Sector" was prepared by the IEA in 2021 at the request of the President of COP 26 (conference of the Parties to the UN Framework Convention on climate Change) and is intended as guidance for the increasing number of countries having pledged to reach net zero. Already in 2021, the 44 countries plus the EU which have made commitments to reach net zero accounted for about 70% of the global CO_2 emissions (IEA 2021c). However, the IEA acknowledges that the complete transformation of our energy system is not an easy task with a narrow pathway but doable and would even bring major benefits for the economy, and most importantly human wellbeing. Unfortunately, only fewer than a quarter of the announced pledges to reach net zero are enshrined in domestic laws and the stated policies fall far short of reaching net zero globally by 2050. This means that countries do not only have to enact strong legislation but the success of the endeavour to reach net zero globally hinges most of all on the implementation of these policies as well as on consumer choices, business decisions in all sectors and private and public investment.

The report is structured into four chapters. The first chapter explores how far targets stated in Nationally Determined Contributions to the Paris Agreement and net zero pledges as well as stated policies would take us in terms of emission reductions. In the following chapter, the Net Zero Emissions by 2050 scenario is presented, what it means for the projected energy demand and mix, and how it depends on uncertain factors such as investment, technology development and behavioural change. Chapter 3 sets out industry-specific pathways for the electricity sector, industry (chemicals, iron and steel, and cement production), transport and buildings, highlighting how these sectors have to change to reach net zero. The final chapter treats the wider implications of reaching net zero for the global economy and employment, the energy industry, citizens' access to affordable energy and their behavioural change, as well as implications for governments concerning energy security, infrastructure, innovation, changes in tax revenue streams and international cooperation.

Already in the summary for policy makers, the report mentions the challenge of the energy transition: the high demand for critical minerals, which is estimated to grow nearly sevenfold only between 2020 and 2030. Rare earth elements are among these critical raw materials playing a key role in low carbon technologies.

1.3 Nd – a rare earth metal and example of a critical raw material

Rare earth elements (REE), also called rare earth metals, are a group of 17 metals comprising the 15 lanthanides together with scandium and yttrium. The lanthanides with atomic numbers of 57 (lanthanum) through 79 (lutetium) are further subdivided into the light rare earth elements (lanthanum cerium, praseodymium, neodymium, promethium, samarium and europium) and heavy rare earth elements (gadolinium, terbium, dysprosium, holmium, erbium, thulium, ytterbium and lutetium). One of them, promethium has no stable isotope and does not occur naturally (Latunussa et al. 2020). Their name rare earth element is misleading as they are not that rare in the earths crust, but rather are rarely found in highly concentrated occurrences and never in metallic form (Walters, Lusty, and Hill 2011). The abundance of individual REEs varies with those having an even atomic number being more abundant than their neighbours in the periodic table, and a general trend of decreasing abundance with atomic number (Haxel, Hedrick, and Orris 2002; Walters, Lusty, and Hill 2011). This means that cerium, the most abundant of the REEs with a crustal abundance of 43 ppm, is much more abundant than for example copper and lead with crustal abundances of 27 ppm and 11 ppm, respectively

(Walters, Lusty, and Hill 2011). Neodymium has a concentration of 20 ppm in the continental crust (Rudnick and Fountain 1995). In minerals, REEs usually occur together, as they can substitute for each other in the crystal lattices due to their similar atomic radius and charge (Walters, Lusty, and Hill 2011). However, minerals usually either contain higher amounts of light or heavy REEs (Haxel, Hedrick, and Orris 2002; Walters, Lusty, and Hill 2011). The economically most important REE ores are carbonatite-associated deposits containing bastnäsite including the Bayan Obo mine in China and the historically important Mountain Pass mine in the USA, as well as so called placer deposits of monazite sands (Long et al. 2010; Walters, Lusty, and Hill 2011; Haxel, Hedrick, and Orris 2002), whereas ion absorption clays or laterites that form from weathering of REE containing rocks are important for their high ore grades and relative abundance of heavy REEs.

Up until the 1980s, the US dominated REE production, but from the 1990s onwards, China took over the leading position (Haxel, Hedrick, and Orris 2002) and now accounts for around 70% of mining after having lost some share of the global mining, but still accounts for 90% of processing of ores to intermediary products such as metals, alloys and magnets (Latunussa et al. 2020). This supply concentration and the high volatility of supply due to the strong state control over REE mining in China are the main reason why REEs are classified as critical raw materials in the EU since the EU first defined critical raw materials in 2010 (European Commission - Report of the Ad-hoc Working Group on defining critical raw materials 2010). Criticality of raw materials also including natural materials such as rubber, are assessed based on two factors: the economic importance and the supply risk (European Commission n.d.). REEs and Nd specifically are especially critical in the form of high performance permanent magnets, NdFeB magnets, which are crucial for the production of wind turbines, EVs and robotics but are also relevant for data storage on hard disk drives (Bobba et al. 2020).

The importance of Nd in wind energy technology and EVs is discussed in further detail in the following two subchapters.

1.4 Wind energy technologies

Wind turbines are used to harness wind to generate electricity. Almost all commercial wind turbines follow the same design principle: the turbine is mounted on a tower made from steel or cast-iron or, in rare cases, concrete and consists of three rotor blades which transmit their movement via the main shaft to a generator directly or via a gearbox to increase the rotation speed (Lacal-Arántegui et al. 2012). The electric generator has two main parts: a fixed stator and a rotor, producing a rotating magnetic field that induces electric energy into the windings of the stator. The magnetic field can either be produced by permanent magnets or by electromagnets (Lacal-Arántegui et al. 2012). Wind turbine sub-technologies can be classified according to their drivetrain configuration (direct drive (DD) or using a gearbox (GB)) and the type of generator (Figure 1). Drive train configuration with a gearbox either increase the rotation to high speed (> 900 rpm) or to medium speed (>80 rpm) (Carrara et al. 2020). In direct drive configurations, the rotor in the generator always rotates at the same speed as the blades at around 20 rpm (Pavel, Lacal-Arántegui, et al. 2017).

Acronyms used to refer to the different sub-technologies are listed in Table 1 and are combined with the acronyms for drive train configuration e.g., DD-PMSG referring to direct drive permanent magnet synchronous generator, or GB-DFIG referring to gearbox doubly-fed induction generator.

Table 1 Acronyms used to refer to different wind turbine generator types.

Generator type	**Acronym**
Permanent magnet synchronous generator	PMSG
Electrically excited synchronous generator	EESG
High-temperature superconductor	HTS
Doubly-fed induction generator	DFIG
Squirrel-cage induction generator	SCIG

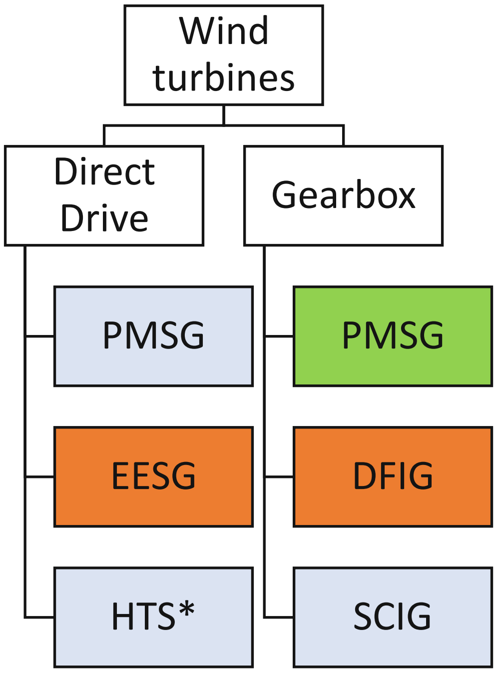


*Figure 1 Wind turbine sub-technologies according to drivetrain configuration and type of turbine as well as according to their main application for offshore (blue), onshore (orange) or both (green).*High-temperature superconductor generators are not commercialized yet.*

Each sub-technology has their advantages and shortcomings making it suitable for the use in different settings either onshore or offshore.

The main advantage of DD wind turbines is their lower maintenance as they avoid failure-prone gearboxes and economic losses due to downtime and repair costs (Lacal-Arántegui et al. 2012). This advantage plays an even bigger role in the offshore wind segment, where the turbines are harder to reach or in larger wind parks (Carrara et al. 2020). However, the lower rotation speed and resulting higher torque require bigger generators for technical reasons (Lacal-Arántegui et al. 2012). In general, wind turbine producers strive to limit the size and weight of the turbines. For this reason, DD turbines use either PMSG or EESG, even though the latter are heavier than PMSG due to the larger amounts of copper needed for windings of the electric excitation and thus not used in offshore wind parks (Pavel, Lacal-Arántegui, et al. 2017).

Another advantage of DD-EESG besides their lower maintenance is the fact that they do not require REE and rely on simple design using available know-how. Moreover, their efficiency is high in partial and nominal loads (Pavel, Lacal-Arántegui, et al. 2017), even though it is still 6% lower than for PMSGs (Månberger and Stenqvist 2018).

Especially in the offshore sector, DD-HTS could replace DD-PMSG because of their lightweight design which could remove about 50% of the generator due to the very high field strength of the superconductor. Moreover, they have an extremely high efficiency outperforming DD-PMSG (Lacal-Arántegui et al. 2012).

In the onshore domain, GB-DFIG are most widely used because of their low manufacturing cost and REE-free design, even though they have a lower efficiency than EESG or PMSG when they operate in partial load at low wind speeds. Furthermore, they are easy to connect to the grid and adaptable to most grid codes, although they fail to comply with the most stringent ones demanding black starts (Pavel, Lacal-Arántegui, et al. 2017; Lacal-Arántegui et al. 2012).

GB-SCIG without a full converter, which meant that the rotation speed had to be kept constant, were widely used in the 1990s, but are now replaced by DFIG (Pavel, Lacal-Arántegui, et al. 2017; Lacal-Arántegui et al. 2012; Carrara et al. 2020). Nowadays, GB-SCIG with a full converter are used to end the dependency on REEs of PMSG (Pavel, Lacal-Arántegui, et al. 2017).

Neodymium is used in wind parks regardless of the sub-technology of turbines used, however, the amounts used vary greatly. DD-PMSG, which have become more and more popular since 2005 (Alves Dias et al. 2020), especially in offshore wind turbines, use the highest amounts of Nd as Nd makes up about 30% of the NdFeB permanent magnets used in the generator, wheighing up to 4 t (Carrara et al. 2020).

1.5 Electric vehicles technologies

Electric vehicles are cars using an electric motor as their main source of propulsion (Pavel, Thiel, et al. 2017). There are a variety of different types of EV: battery electric vehicles (BEV), which rely only on electricity stored in an onboard battery as an energy source, plug-in hybrid electric vehicles (PHEV) with an internal combustion engine to recharge the battery, and fuel cell electric vehicles (FCEV), which do not store electricity in a battery but produce it onboard usually from hydrogen through a fuel cell. Hybrid electric vehicles, where the main propulsion comes from an internal combustion engine and the electric motor merely supports it as a secondary source of propulsion, are not counted as EVs (Pavel, Thiel, et al. 2017).

Currently, more than 90% of all EVs rely on NdFeB permanent magnets for their electric traction motors (Pavel, Thiel, et al. 2017) and also in future these high performing magnets are expected to be the dominant technology with 80% of all EVs produced using them (Latunussa et al. 2020). One reason for the preference of car makers for NdFeB magnet technologies are the very strong magnetic field of NdFeB magnets which allows for a compact design of the motor, which is especially for hybrid cars where two drivetrains have to fit into the limited space of a car (Bobba et al. 2020; Pavel, Thiel, et al. 2017). Moreover, permanent magnet synchronous motors, the main technology of PM-based motors, supply high torque and are easy to be controlled. Another advantage over induction motors, which substitute the permanent magnet by electro magnets, is the higher efficiency since no electricity is needed to produce the electric field (Pavel, Thiel, et al. 2017).

However, the volatility of REE supply and prices for NdFeB magnets caused by Chinese export restrictions, have encouraged the use of technologies which do not rely on REEs (Latunussa et al. 2020; IEA 2021b). Already today, there are EVs on the market which rely on induction motors that do not use any REEs (e.g. Tesla model S, Audi e-tron) or significantly reduce the amount of NdFeB magnets through optimised design (IEA 2021b; Pavel, Thiel, et al. 2017). Switched reluctance motors are also a promising technology without REEs, however they are still in the prototype phase (IEA 2021b; Pavel, Thiel, et al. 2017).

1.6 Recycling of Nd from NdFeB permanent magnets

NdFeB permanent magnets are the main application of Nd and their market share and absolute production numbers are growing fast due to the growth in wind turbine and EV use (Ciacci et al. 2019). Recycling of NdFeB magnets is important as it diminishes the dependence on primary Nd subject to high price volatility and demand could soon exceed supply from mining (Latunussa et al. 2020). However, currently the recycling rate of Nd is only about 1% and only very few industrial scale recycling facilities for the recovery of Nd exist (Latunussa et al. 2020). The obstacles for recycling include the lack of separate collection for recycling of NdFeB magnet containing products, the small size of magnets in many applications such as hard disk drives or acoustic transducers and lack of automated dismantling. In addition, the variety of the composition of magnets complicate generic recycling processes, and low REE prices in the past discourage recycling (Latunussa et al. 2020). A considerable amount of NdFeB magnets is lost even for appliances and vehicles that are collected for recycling because the conventional shredding procedures fail to separate the magnets which stick to the ferrous metal fraction and end up in recycled steel (Habib 2015; Widmer et al. 2015; Yang et al. 2016).

Permanent magnet waste is generated during manufacturing of the magnets, where 15% - 30 % or even up to 73 % of the raw material become scrap called swarf (Kumari et al. 2018; Chowdhury et al. 2021), as well as at the end of life of products containing PMs. In general, two different routes exist for the recycling of NdFeB magnets: direct recycling and indirect recycling. Direct recycling refers to the reuse of the magnets without separating the contained elements as is done in indirect recycling (Latunussa et al. 2020). Direct recycling is a suitable strategy for the internal recycling of swarf in the production process (Schulze and Buchert 2016). Finished magnets contain a Ni-coating to protect them from corrosion, which would deteriorate the quality of the magnet if remelted during direct recycling. Therefore, indirect recycling is the preferred option for off-quality magnets that cannot be sold as well as for small magnets recovered from end-of-life (EOL) products (Schulze and Buchert 2016), whereas large magnets like the ones used in EVs and wind turbines can be recycled directly in an economic way (Zhang et al. 2020; Yang et al. 2016).

For indirect recycling several technologies exist, which are generally able to recover more than 80% of the contained REEs at high purity (Yang et al. 2016). Their main advantage over direct recycling is that they are applicable to all types of magnets with different compositions (Zhang et al. 2020; Yang et al. 2016). However, depending on the technology, they are very energy intensive, consume large amounts of chemicals, or produce large amounts of waste (Zhang et al. 2020; Yang et al. 2016). Indirect recycling technologies can be classified in two groups: hydrometallurgical and pyrometallurgical methods. For hydrometallurgical methods the first step is always leaching, which dissolves the REEs or the whole magnet, in some cases after a roasting step that converts the metals into oxides (Yang et al. 2016). After leaching, the REEs are separated via solvent extraction using organic extractants, ionic liquid extraction or via precipitation (Zhang et al. 2020).

For pyrometallurgical methods, different technologies can be distinguished: (i) roasting as a preparatory step for more efficient hydrometallurgical treatment, (ii) melt processing where the REEs of the magnets are selectively dissolved into a liquid metal phase (liquid metal extraction), into a molten chloride or fluoride salt (molten salt extraction), into a molten slag (molten slag extraction), and (iii) electrochemical processing in electrochemical reactors (Yang et al. 2016).

1.7 Research Question and goal of the study

The overall research question to be answered in this thesis is: "*Can the Nd-demand required for the goal to reach net zero by 2050 be met according to projections of primary production (i.e. mining) and secondary production (i.e. recycling)?*". The flagship report "Net Zero by 2050 – A Roadmap for the Global Energy Sector" by the IEA and the scenario outlined therein is used as a basis to answer the question.

Several sub-questions concerning the Nd-demand to reach net zero, the Nd-metabolism and supply risks of Nd, arise which have to be answered too. These sub-questions are:

(i) *How high does the newly installed wind generation capacity have to be to reach the goals of the Net Zero by 2050 Roadmap, taking into account retiring wind turbines?*

(ii) *What will the number of cars on the road be according to the Net Zero by 2050 Roadmap and how many cars have to be sold annually to reach this number?*

(iii) *What are the technology shares of wind turbine technologies and the shares of different EVs of the annually installed or sold wind turbines and cars?*

(iv) *What is the Nd-intensity of each of these sub technologies of wind turbines and EVs?*

(v) *What is the recycling potential of Nd - how much Nd is potentially going to be recovered from wind turbines and EVs reaching their end of life each year?*

(vi) *How high is the current and possible future primary production of Nd?*

2. Methods

In the methods section, it is described how the sub-questions of the research questions were answered and what assumptions were made.

In principle, this study conducts a global dynamic material flow analysis for Nd in wind energy and EVs for the time-period of 2020 to 2050. By incorporating technical parameters such as the lifetime, technology shares and material intensities into this technology -specific model, different scenarios are explored.

Annex 1 includes the MatLab code used for the modelling and plotting of graphs.

2.1 *Nd Demand for wind turbines*

Since the Net Zero by 2050 Roadmap only gives, the installed wind power capacity, this value had to be converted to the mass of Nd required to instal the wind turbines. This was done through the Nd intensity of wind turbines. However, as there are very different designs requiring different amounts of Nd (e.g. Carrara et al., 2020), the technology share of the installed capacity has to be taken into account too. As can be seen in the structure of the results section, the Nd demand for wind turbines was assessed in 3 steps: first, the Nd intensity of wind turbines of different technologies, second the required newly installed wind power capacity each year, and third, the share of different wind turbine technologies for the period of 2020 to 2050 were found to subsequently model the Nd demand.

To find the Nd intensity of wind turbines, the mass of Nd per unit of installed capacity, the literature was reviewed. The results of the literature review for the Nd intensity of different types of wind turbines are listed in Table 4 in the Results section. As described in the introduction, not all wind turbine technologies rely on NdFeB permanent magnets for their generators. However, they still use smaller quantities of permanent magnets, as magnets are also used to attach internal fixtures in the towers (Carrara et al. 2020). Whereas most sources only give values for permanent magnet generator type turbines with a direct drive or gearbox setup, Carrara et al., (2020) also estimated the Nd intensity of other common turbine technologies. Most studies base their estimation of the Nd content of wind turbines on the mass of the permanent magnet and an average Nd content for these NdFeB magnets. However, the Nd content reported in the literature varies a lot from 20% to up to 32% (Viebahn et al. 2015). Even though most authors use values between 27% (e.g. Li et al., 2020) and 31% (e.g. Viebahn et al., 2015), this still makes a noticable difference of about 15% for the calculated mass of Nd.

Next, the required annual capacity additions of wind power were modelled. The IAE states in its Roadmap to Net Zero 2050, that annual capacity additions for wind energy have to reach 114 GW (5 of which offshore) in 2020, 390 GW (80 of which offshore) by 2030, and would slightly go down to 350 GW annual added capacity (70 of which offshore) by 2050. Total installed wind capacity would reach 737 GW in 2020, compared to 623 GW in 2019, 3,101 GW in 2030, 6,252 GW in 2040 and 8,265 GW in 2050, increasing the share of wind power capacity from 9% in 2020 to 21% in 2030 and 25%

in 2050 (IEA 2021c). This translates into a compound annual average growth rate of 15% between 2020 and 2030 or 8.4% between 2020 and 2050 (IEA 2021c).

To interpolate the annual values of the total installed capacity between 2020 and 2050, the MatLab polyfit function was used to fit a third order polynomial function between the values given in the Net Zero 2050 report with intervals of 5 years. For offshore wind capacity, linear growth was assumed as an approximation. Based on that, the annual capacity growth was calculated as the difference between two consecutive years. A polynomial function was chosen as its shape reflects the forecasted capacity development and to avoid non-continuity in the capacity growth curve. Since onshore and offshore wind turbines are modelled separately, the respective capacity growth had to be calculated.

Since the annual growth equals the newly installed capacity minus the retired capacity, the retired capacity had to be calculated too. To do this, a lifetime function in the form of a probability density function of a Weibull distribution was used, a commonly used function to estimate lifetime of machines, including wind turbines (Welte and Wang 2014). Weibull functions have two to three parameters, a shape parameter α determining the skewedness or shape, and a scale parameter β defining the scale of the values along the x-axis, plus in some cases a location parameter used to shift the whole distribution (Melo 1999). The Weibull distribution is given by:

$$f(x) = \frac{\beta}{\alpha^{\beta}} x^{\beta-1} \exp\left(-\left({}^{x}/_{\alpha}\right)^{\beta}\right)$$

Figure 2 visualizes the frequency distributions of Weibull functions with different parameters.

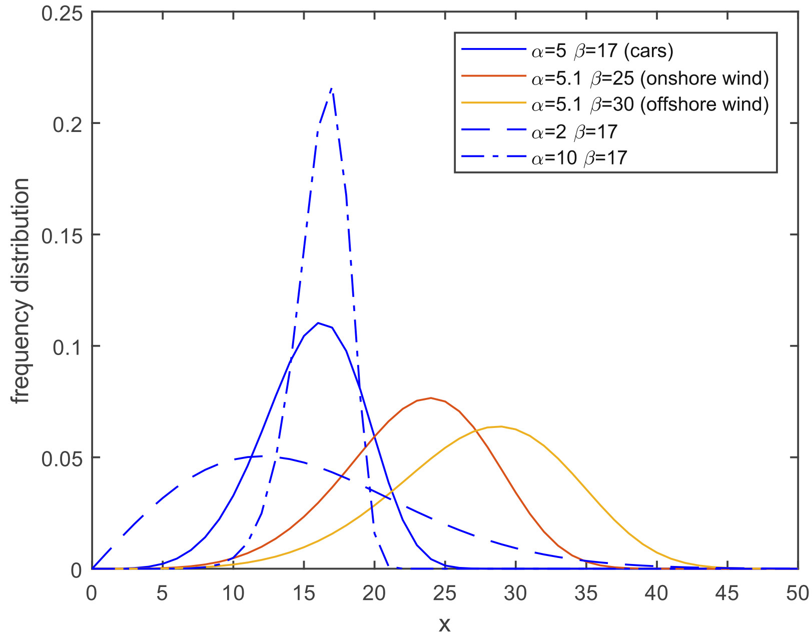


Figure 2 Frequency distributions for Weibull functions with different parameters as used for the lifetime modelling in this study 8solid lines) and to exemplify the effect of different shape factors (dashed and dash-dot).

The shape parameter used for wind turbines in this study is 5.1, a value empirically derived for wind turbines with gearboxes (Gray and Watson 2010). The scale factor was set equal to the expected lifetime of 25 years for onshore and 30 years offshore wind turbines (Carrara et al. 2020). The resulting Weibull distribution (Figure 2) gives the fraction of wind turbines reaching their end of life each year after the installation of the batch of wind turbines. Based on this, the wind generation capacity retiring each year is calculated. It is important to note, that the number of wind turbines reaching their end of life is calculated based on the annual capacity growth and not the newly installed capacity each year. Therefore, the retiring capacity is a lower estimate, especially for the later years, when the newly added capacity starts to deviate more from the capacity growth. However, given the long lifetime of wind turbines the effect is assumed to be negligible. In a last step, the added, i.e., newly installed capacity, is calculated as the sum of the retiring capacity and the capacity growth for onshore and offshore wind.

The technology shares used to explore different scenarios of future Nd-demand were taken from two different sources: Carrara et al. (2020) and IEA (2021a). However, as the data by the latter only makes predictions until 2040, a continuation of the trend from 2030 to 2040 is assumed for onshore wind under the baseline scenario, no change in technology share is assumed for the restricted REE supply scenario onshore and the baseline scenario offshore, and for the restricted REE supply scenario offshore, it is assumed that DD-HTS gain 10% at the expense of DD-PMG. This follows the trends predicted by Carrara et al. (2020). It is important to note, that the technology shares in IEA (2021a) were only presented in figures and the values had to be read off the figures, which introduces some error.

2.2 Nd Demand for EVs

The number of EVs having to be produced to reach net zero globally is not directly given in the Net Zero 2050 Report. Instead, the vehicle kilometers (vkm) travelled globally by passenger cars are stated. However, since the share of households owning 1, 2 or 3+ cars is given for 2050 for a scenario with and without behavioural change, the total number of cars can be calculated and from that the number of cars per vehicle kilometer (neglecting households owning more than 3 cars and counting them as owning 3 only). This results in a factor of 95 cars per million vkm without behavioural change (10,573 km per vehicle per year) and 47 cars per million vkm after behavioural change (21,147 km per vehicle per year). For comparison, the global average kilometers driven per car annually was 18,000 km in 2008, with regional differences ranging from 8,276 km (Japan) to 26,000 (China) (Deetman et al. 2018).

Since only vkm for the years 2019, 2020, 2030, 2040 and 2050 are given, the annual data for 2021 to 2050 were interpolated with a polynomial fit using MatLab Polyfit function to fit a square function. For the scenario without behavioural change, a rebound of car sales to 2019 levels in 2021 was assumed.

Knowing the total stock of cars each year, the growth in stocks can be calculated, and - by subtracting the cars retiring - the annually sold cars.

The number of cars reaching their end of life is calculated based on a Weibull lifetime function with a shape factor of 5 and a scale factor equal to the expected lifetime of 17 years (see Figure 2) as used in the Net Zero 2050 Report and by (Dworak, Rechberger, and Fellner 2022). However, since car sales data are only known from 2005 onwards and the integral of the Weibull function only reaches 1 after 27 years, a fixed lifetime of 17 years was assumed to calculate the number of retiring cars for the years 2021 to 2031. For the years 2032 to 2050, the number of retiring cars was calculated based on data from the lifetime distribution of the previous 27 years. This was done for the scenario without behavioural change as well as for the scenario with gradual behavioural change.

However, as this study is only interested in EVs, the number of EVs sold annually has to be modelled, which is done via the share of BEVs, PHEVs and FCEVs of car sales each year. According to the roadmap laid out in the Net Zero 2050 Report, no internal combustion engine cars (ICE) will be sold globally from 2035 on. The technology share of light duty vehicles (i.e. cars and vans) sold in 2020, 2030 and 2050 according to the roadmap is given in Table 2. It was assumed for further calculations, that change in vehicle type is linear and that the technology share of 2050 is already reached in 2035 and then stays constant.

Table 2 Technology shares of Battery electric vehicles, Plug-in hybrid vehicles and Fuel cell electric vehicles in the sale of light duty vehicles (cars and vans) according to the Net Zero 2050 Report.

	2020	2030	2050
Battery electric	2.80%	54.60%	90.20%
Plug-in hybrid electric	1.20%	7.00%	0.42%
Fuel cell electric	0.02%	2.90%	9.30%

Next, the Nd intensity of each of the EV subtechnologies is assessed by conducting a literature review. Since there is a lot of uncertainty about the Nd intensity of EVs given their constant development, a low and high estimate for each technology is considered for the calculation of the Nd demand for EVs. The values derived from the literature review and used for further calculations are given in Table 3.

Table 3 Low and high Nd intensities for BEV, PHEV and FCEV used for the modelling of Nd demand in EVs.

	g Nd/car (low)	g Nd/car (high)
BEV	567	2 250
PHEV	473	1 460
FCEV	473	2 920

Based on these Nd intensity and the number of BEVs, PHEVs and FCEVs sold annually, the Nd demand is calculated.

2.3 Nd Reserves and future production capacities

The assessment of Nd reserves and future production capacities is based on a literature review of mineral production statistics: the Mineral Commodity Summaries by the U.S. Geological Survey, the World Mineral Production report by the British Geological Survey and the World Mining Data report by the Austrian Federal Ministry for Agriculture, Regions and Tourism for the International Organizing Committee for the World Mining Congresses (U.S. Geological Survey 2022; Idoine et al. 2022; Reichl and Schatz 2022).

However, as these reports only publish data on (mixed) rare earth oxides (REO) and not on individual rare earth metals, the Nd production is inferred from the reported REO equivalents by assuming 16% of the REOs to be Nd-oxide and 1.17 kg of Nd-oxides required to produce 1 kg of Nd (Blagoeva et al. 2016).

Furthermore, illegal REE mining in China was also accounted for based on data of Geng et al. (2020) and Yao et al. (2021), who performed static and dynamic material flow analyses for Nd in China for 2016 and the period of 2000 to 2050 respectively.

2.4 Nd Recycling Potential

In order to calculate the potential contribution of secondary Nd to meet the annual demand, firstly the annually released Nd amounts from wind retiring turbines and EVs are calculated and then transfer coefficients applied for the efficiency of disassembly and recycling.

The released amounts of Nd from stocks of EVs are estimated based on the expected lifetime and therefore equal to the demand 17 years (one expected lifetime) before. Historic Nd demand is modeled based on the stock of BEVs and PHEVs given by IEA (2020) and the stock of FCEV of 2020 was assumed to have been added all in that year (IEA 2021a). It is assumed that no EVs were sold before 2010, therefore the first EVs retire in the year 2027. Released stocks were modelled for all considered scenarios, however, since historic data is underlying most of the calculation, the scenarios only differ from 2038 on.

Given the long lifetime of wind turbines (25 years onshore and 30 years offshore), the amount of released Nd would only differ under the different scenarios in the years from 2045 to 2050 for onshore if the same methodology as for EVs with a static lifetime is applied.

Therefore, a different modelling approach was used: the demand for Nd under each scenario was multiplied with the Weibull lifetime distribution and then the released stocks of Nd calculated from the lifetime distribution. The historic Nd demand for wind turbines was calculated based on the technology shares given by (IEA 2021b) for the year 2010 applied to all wind turbines installed before 2020. It was assumed that no wind turbines were installed before 1997.

To find the applicable transfer coefficients or efficiency of disassembly and recycling, the literature was reviewed; the results of the literature review are summarised in Table 13. An overview over the different technologies to recycle NdFeB permanent magnets from EOL wind turbines and EVs is given in the Introduction and the assumptions and factors used for wind turbines and EVs respectively are described with the results. It was assumed that all the Nd embedded in wind turbines and EVs are NdFeB permanent magnets or have the same recycling potential as NdFeB magnets. For wind turbines the assumption that all Nd is present in permanent magnets is expected to be valid and other uses negligible. For EVs, Nd is also present in smaller amounts in printed wiring boards of consumer electronics and air conditioning of the car, as well as in capacitors, however in masses 1-2 orders of magnitude lower than used for the permanent magnets of the electric motor (Cullbrand and Magnusson 2011; Widmer et al. 2015).

3. Results

This section describes the findings of the literature reviews and the model results. First, findings concerning the Nd demand for wind turbines and EVs are presented, followed by the reserves and production capacities of Nd and finally the recycling potential of Nd from end-of-life EVs and wind turbines.

3.1 Nd Demand for wind turbines

3.1.1 Nd intensity in wind turbines

Analyzing the different reported Nd intensities, shows that until 2018, studies agree on ~200 kg Nd per MW installed DD-PMSG while more recent studies report lower values of ~ 180 kg Nd per MW, reflecting technological advance. For other technologies, the Nd intensities reported in the literature vary much more and often estimates are given for a mix of technologies or for onshore and offshore wind turbines (see Table 4).

For further calculations, the most recent and detailed data from Carrara et al. (2020) are going to be used (marked bold in Table 4). They assessed the Nd intensity for four technologies (DD-PMSG, GB-PMSG, DD-EESG, GB-DFIG) and for a lack of better data for DD-HTS and GB-SCIG they used the intensities of DD-EESG and GB-DFIG respectively since they are closest in design.

Table 4 Material intensity of permanent magnets (PM) and Nd per MW installed capacity for direct drive (DD) and gear box (GB) wind turbines. Where only the permanent magnet intensity was given, the Nd intensity was calculated based on 30% Nd content of NdFeB permanent magnets.

Source	**material**	**DD [kg/MW]**	**GB [kg/MW]**	**comment**
(Lacal-Arántegui 2015)	PM	650	160 (mid speed) 80 (high speed)	Given in PM
	Nd	195	48 (mid speed) 24 (high speed)	
(Månberger and Stenqvist 2018)	Nd	200	20 – 50	GB 75% - 90% less Nd than DD
(Shaw and Constantinides 2012)	PM	600	200	Given in PM
	Nd	200	60	
(Habib and Wenzel 2014)		150		Given in Nd, average of technologies
(Habib and Wenzel 2016)	Nd	200		Given in Nd
(Yang et al. 2016)	PM	250 - 600		Given in PM, technology not specified
	Nd	75 - 180		
(Constantinides 2016)	PM	600+ (old ≤ 4MW); 500 (new ≥ 5MW)	200	Given in PM
	Nd	180+ (old ≤ 4MW); 150 (new ≥ 5MW)	60	
(Viebahn et al. 2015)	PM	650	160 (mid speed) 80 (high speed)	From (Lacal-Arántegui 2015)
	Nd	201.5	49.6 24.8	Based on 31% Nd
(Deetman et al. 2018)		119 – 198 (“offshore”)	0 -41 (“onshore”)	Given in Nd
(Li et al. 2020)	PM	650	120	Based on (Lacal-Arántegui 2015)
	Nd	175.5	32.4	Based on 27% Nd
(Moss et al. 2013)	PM	700		Based on industry sources and reports

	Nd	203		Based on 29% Nd
(Carrara et al. 2020)	**Nd**	**180**	**51**	**28 for DD-EESG (and DD-HTS); 12 for GB-DFIG (and GB-SCIG)**
(Tokimatsu et al., 2018)	Nd	124 - 168		Technology not specified
(Elshkaki and Graedel 2013)	Nd	124		For offshore wind turbines (0 for onshore)

3.1.2 Newly installed wind power capacity to reach Net Zero 2050

As described in the Methods section, the newly installed wind power capacity was modeled based on the total installed capacity given in the Roadmap to Net Zero 2050 for every fifth year 2020 to 2050. The polynomial fit used to interpolate the missing values to get annual installed capacity is shown in Figure 3.

The values fitted for are all within less than 3% difference from the fitted curve, except for the 2025 value, which is 9.6% off (Figure 3).

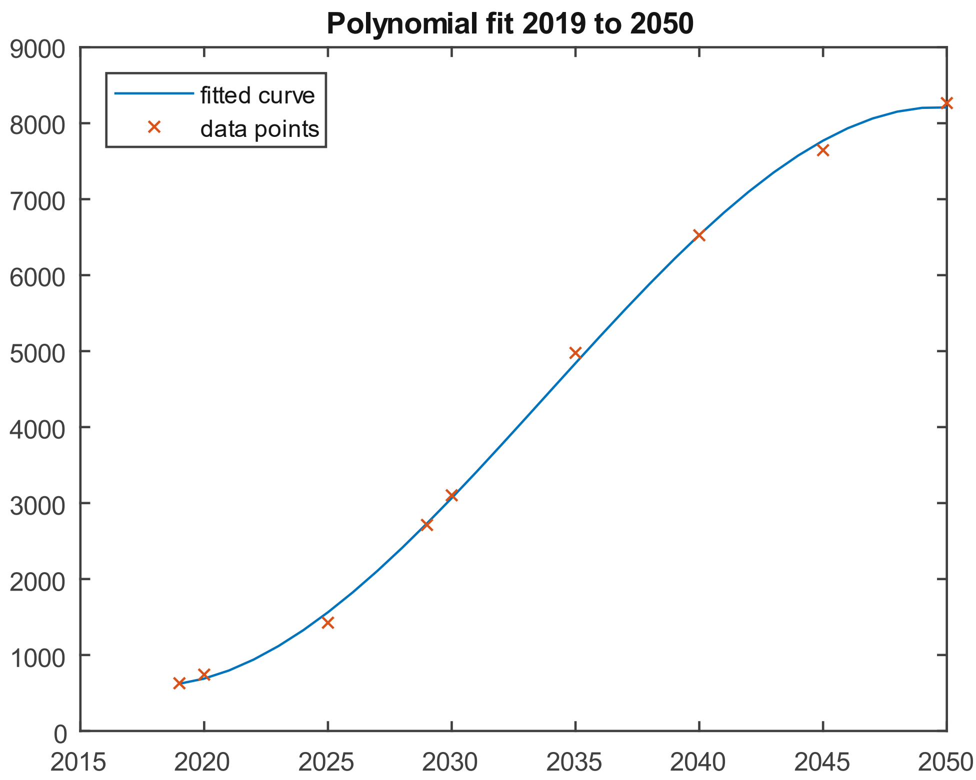


Figure 3 Polynomial fit for the total installed capacity 2019 to 2050 (in GW).

Furthermore, added wind generation capacity was calculated for onshore and offshore wind based on the annual capacity growth and the retiring capacity according to a Weibull lifetime-function. The results are shown in Figure 4 for total wind generation capacity, Figure 5 for onshore wind, and Figure 6 for offshore wind.

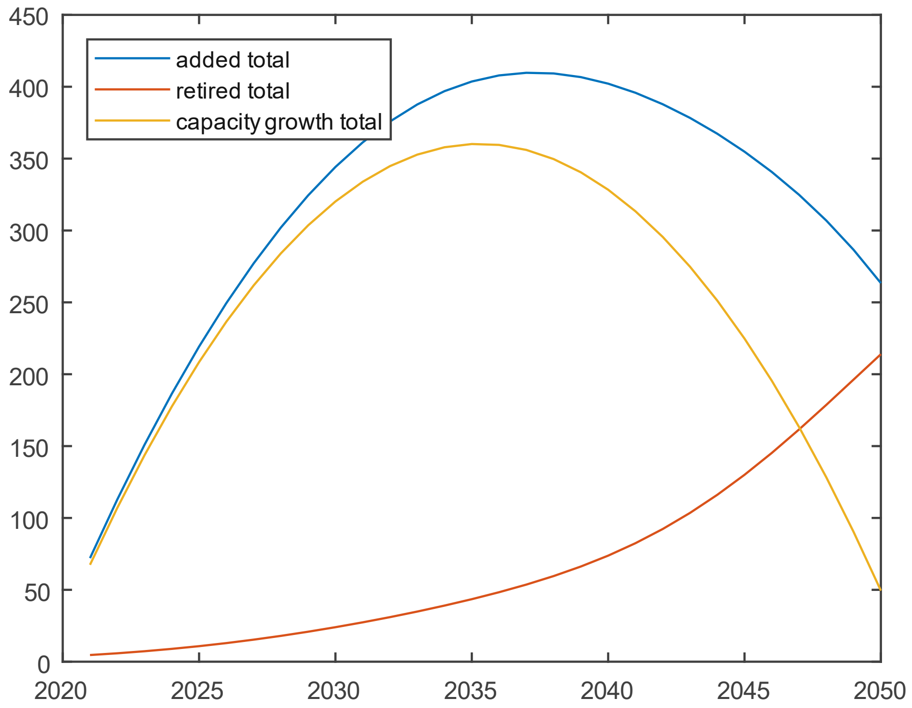


Figure 4 Total wind generation capacity growth (in GW), added capacity and retired capacity for the years 2021 to 2050.

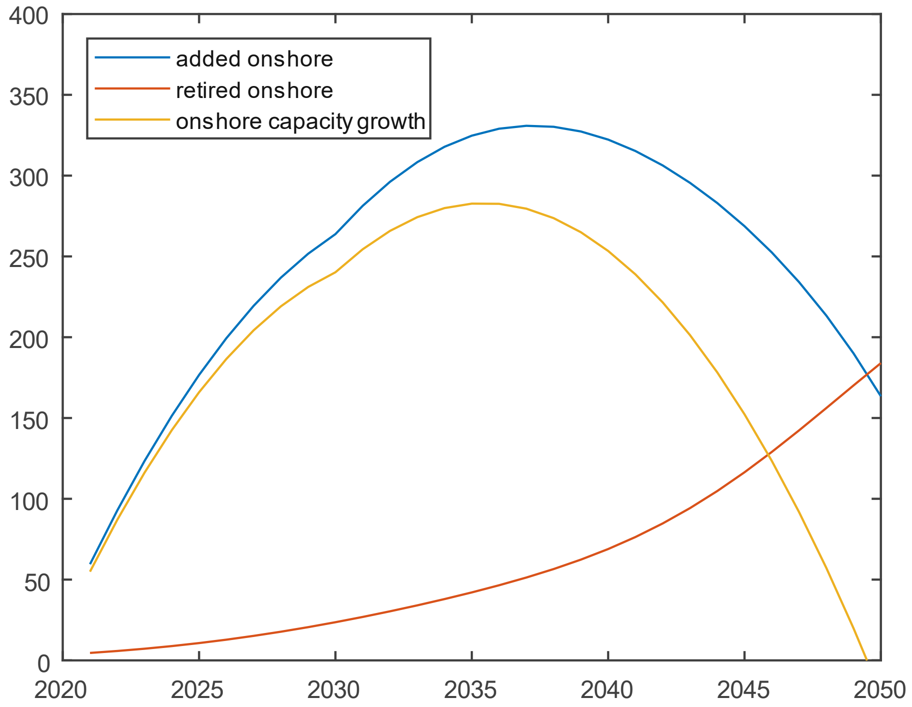


Figure 5 Onshore wind generation capacity growth (in GW), added capacity and retired capacity for the years 2021 to 2050.

Total added wind generation capacity (Figure 4) as well as added onshore capacity (Figure 5) peak in 2037, shortly after capacity growth reaches its peak. Whereas added capacity and capacity growth are nearly the same before 2030, they diverge more and more as the number of retiring wind turbines having to be replaced rises continuously and with an increasing rate.

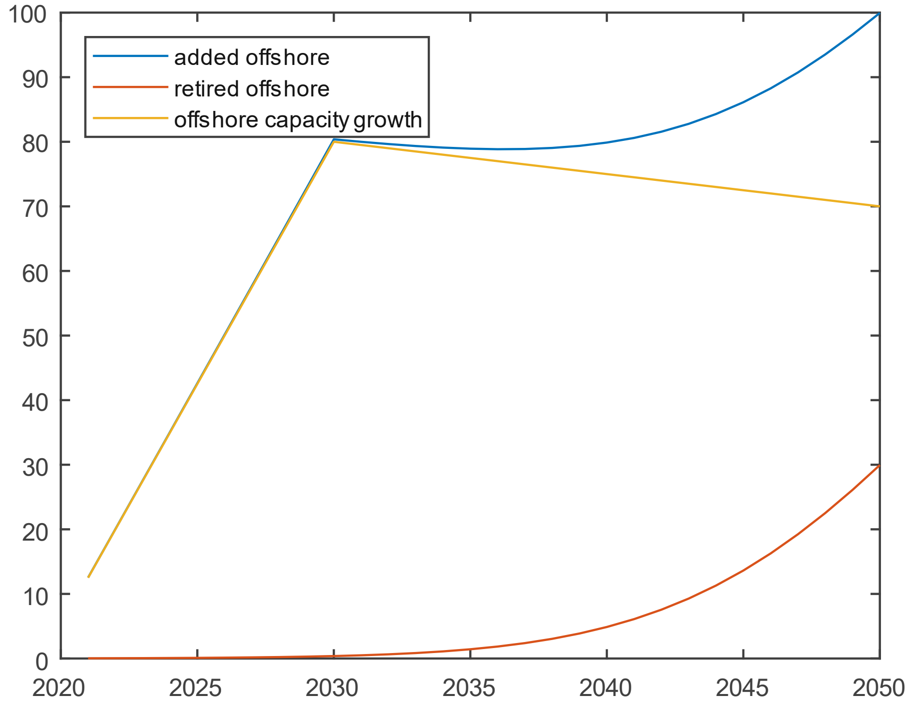


Figure 6 Offshore wind generation capacity growth (in GW), added capacity and retired capacity for the years 2021 to 2050.

Following the values given in the Roadmap to Net Zero 2050 report, capacity growth reaches a peak in 2030 and then slowly decreases. Added capacity however stays nearly constant between 2030 and 2037. When the number of retiring wind turbines starts to increase rapidly around 2040, the added capacity also increases correspondingly.

3.1.3 Share of wind turbine technologies 2020 to 2050

The share of wind turbine technologies has changed continuously in the past and the future development is hard to predict as it depends on uncertain factors like innovation and technological advance on the one hand and price development of key raw materials on the other hand. However, many studies agree on general trends based on the advantages of each technology. For instance, direct drive configurations, which require less maintenance than generators with a gearbox and permanent magnet turbines, which are lighter than electric magnets and more efficient, especially when running below rated power, are better suited for large offshore windfarms, whereas the heavier but cheaper generators with a gearbox and electric magnets remain competitive onshore. It makes sense therefore, to consider multiple scenarios and look at onshore and offshore wind energy separately. Since the Net Zero 2050 Report does not specify the sub technology of wind energy but only total added capacity for onshore and offshore wind power, the technology share predictions from Carrara et al. (2020) and IEA (2021a) are used to explore different scenarios. In total 5 Scenarios were considered each for onshore and offshore wind: (i) the Low Demand Scenario (LDS) of Carrara et al. (2020), (ii) Medium Demand Scenario of Carrara et al. (2020) and (iii) High Demand Scenario Carrara et al. (2020), as well as the (iv) Base Case (IEA baseline) of IEA (2021a) and (v) Constrained REE supply Case(IEA constrained REE) of IEA (2021a). The technology shares for the years 2030, 2040 and 2050 under each scenario are shown in Figure 7.

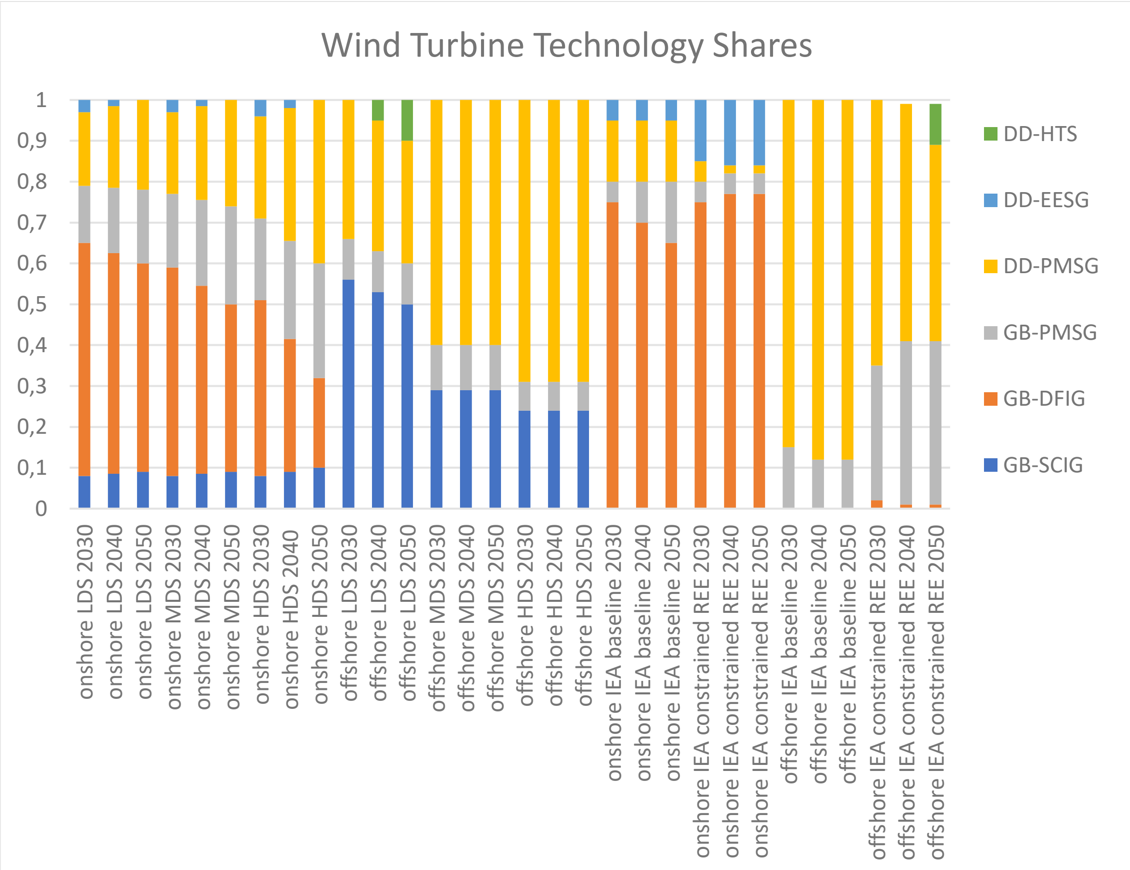


Figure 7 Wind turbine technology shares under the scenarios Nd demand was modelled for.

3.1.4 Nd demand for wind turbines to reach Net Zero 2050

The demand for Nd for wind turbines was calculated for 5 scenarios, the low, medium and high demand scenarios from Carrara et al. (2020) and the baseline scenario and restricted REE-scenario from IEA (2021a). To achieve this, the newly installed onshore and offshore wind capacity of each year, the sub-technology share under each scenario and the Nd intensity for the different sub-technologies were used.

The results are given in Table 7 and visualized in

Figure 8.

The graphs for Nd demand reflect the shape of the graphs of the added wind generation capacity. However, the different scenarios with their distinct technology shares gain different results. For offshore wind turbines and total wind turbines, LDS has the lowest Nd demand, whereas for onshore, IEA constrained REE is lowest. The highest Nd demand is observed with the HDS scenario except for offshore, where the IEA baseline scenario shows higher Nd demands. For onshore and total Nd demand for wind turbines, the MDS scenario is higher than the IEA baseline. For offshore wind turbines, the IEA constrained REE scenario is curiously even higher than the HDS scenario about 2033, and it sinks even below the MDS scenario after 2045.

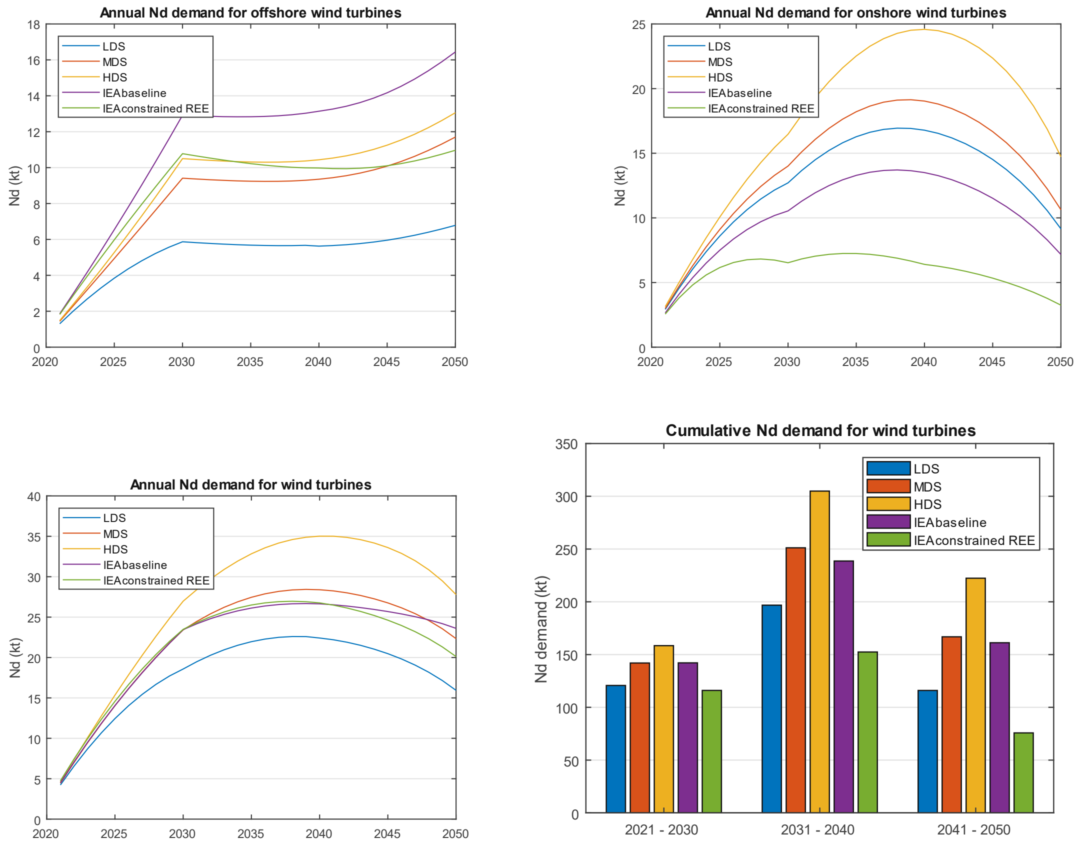


Figure 8 Annual Nd demand for offshore-, onshore and total wind turbines under 5 different scenarios, as well as cumulative demand over 10-year perios (2021-2030, 2031 – 2040, 2041 – 2050).

Comparing the obtained results with the expected demand for Nd estimated by IEA (2021a) for a stated policy and sustainable development scenario (Table 5), it is interesting to note, that the modelled demand based on the Nd intensities given by Carrara et al. (2020) are already ~80% higher for 2020 than the data given by IEA (2021a) even though the IEA (2021a) numbers are also based on Nd intensities of Carrara et al. (2020), besides the ones of Månberger and Stenqvist (2018) and private communication with companies. However, they are still in the same order of magnitude. It is important to note that the sustainable development scenario is not equal to the Net Zero 2050 Roadmap.

Table 5 Comparison of modelled values for annual Nd demand (int t) in wind turbines and literature data from IEA (2021a).

	2020	2030	2040
IEA stated policy scenario	3 138	6 132	6 097
IEA sustainable development scenario	3 138	8 536	8 986
total LDS	5 897	18 580	22 412
total MDS	6 023	23 420	28 390

total HDS	6 035	26 974	35 019
total IEA baseline	5 637	23 452	26 645
total IEA constrained REE	5 637	17 306	16 382

If the cumulative amount of Nd demanded for wind energy between 2021 and 2050 is compared to published demand predictions from the literature, it can be seen that the results of this study are within the range of the literature values and very similar to the results of Li et al., (2020) (see Table 6).

Table 6 Review of different cumulative global Nd demand range projections from 2021 to 2050 from Li et al., 2020. (in kt)

	Lower estimate	Upper estimate
(World Bank 2020)	80	230
(World Bank 2017)	30	400
(Watari, Nansai, and Nakajima 2020)	250	740
(Månberger and Stenqvist 2018)	95	1208
(Elshkaki and Graedel 2013)	30	170
(Valero et al. 2018)	250	250
(de Koning et al. 2018)	408	408
(Habib and Wenzel 2014)	45	375
(Li et al. 2020)	460	902
This study	*445*	*814*

Table 7 Annual Nd demand (in t/year) for wind turbines under 5 different scenarios.

	2020	2021	2022	2023	2024	2025	2026	2027	2028	2029
onshore LDS	5 360	2 921	4 544	6 031	7 382	8 600	9 685	10 638	11 459	12 150
onshore MDS	5 449	2 994	4 696	6 284	7 755	9 107	10 339	11 447	12 430	13 285
onshore HDS	5 449	3 133	4 985	6 764	8 462	10 070	11 580	12 985	14 274	15 440
onshore IEA baseline	4 904	2 648	4 081	5 365	6 504	7 504	8 367	9 098	9 702	10 181
onshore IEA constrained REE	4 904	2 557	3 799	4 802	5 584	6 161	6 549	6 763	6 821	6 738
offshore LDS	537	1 304	2 016	2 677	3 286	3 845	4 352	4 807	5 212	5 566
offshore MDS	574	1 442	2 310	3 183	4 059	4 940	5 824	6 713	7 607	8 506
offshore HDS	585	1 484	2 401	3 339	4 297	5 277	6 278	7 300	8 344	9 411
offshore IEA baseline	734	1 856	2 996	4 158	5 341	6 546	7 774	9 023	10 296	11 592
offshore IEA constrained REE	734	1 822	2 890	3 938	4 968	5 980	6 974	7 950	8 909	9 851

	2030	2031	2032	2033	2034	2035	2036	2037	2038	2039
onshore LDS	12 711	13 664	14 500	15 216	15 810	16 279	16 623	16 842	16 940	16 919
onshore MDS	14 009	15 106	16 079	16 924	17 637	18 212	18 650	18 949	19111	19 139
onshore HDS	16 473	17 955	19 312	20 532	21 606	22 523	23 277	23 862	24 274	24 515
onshore IEA baseline	10 540	11 293	11 947	12 498	12 946	13 290	13 530	13 668	13 707	13 651
onshore IEA constrained REE	6 529	6 825	7 041	7 180	7 246	7 245	7 180	7 058	6 884	6 663
offshore LDS	5 869	5 821	5 777	5 739	5 706	5 681	5 663	5 655	5 657	5 671
offshore MDS	9 411	9 367	9 326	9 290	9 262	9 242	9 233	9 236	9 256	9 293
offshore HDS	10 501	10 451	10 406	10 366	10 334	10 312	10 302	10 306	10 327	10 370
offshore IEA baseline	12 913	12 882	12 857	12 839	12 830	12 833	12 850	12 886	12 944	13 027

offshore IEA constrained REE	10 776	10 652	10 532	10 420	10 315	10 221	10 139	10 070	10 019	9 987	

	2040	2041	2042	2043	2044	2045	2046	2047	2048	2049	2050
onshore LDS	16 784	16 540	16 190	15 738	15 182	14 518	13 739	12 831	11 778	10 559	9 150
onshore MDS	19 037	18 809	18 458	17 987	17 394	16 674	15 817	14 807	13 623	12 241	10 631
onshore HDS	24 583	24 482	24 212	23 771	23 156	22 356	21 354	20 125	18 639	16 855	14 730
onshore IEA baseline	13 503	13 270	12 953	12 556	12 080	11 521	10 873	10 128	9 273	8 292	7 167
onshore IEA constrained REE	6 404	6 264	6 086	5 872	5 624	5 339	5 016	4 652	4 240	3 774	3 248
offshore LDS	5 628	5 658	5 705	5 769	5 853	5 958	6 084	6 230	6 398	6 584	6 786
offshore MDS	9 353	9 437	9 549	9 693	9 870	10 084	10 335	10 624	10 950	11 311	11 703
offshore HDS	10 436	10 530	10 655	10 815	11 013	11 252	11 532	11 854	12 218	12 621	13 058
offshore IEA baseline	13 141	13 260	13 418	13 619	13 868	14 168	14 521	14 927	15 386	15 893	16 443
offshore IEA constrained REE	9 978	9 946	9 940	9 964	10 018	10 104	10 221	10 369	10 545	10 746	10 966

3.2 Nd Demand for EVs

3.2.1 Nd intensity in EVs

The literature review reveals that there is no agreement on the Nd intensity of different types of cars and the estimates vary widely (see Table 8). There are big differences also within the same type of car (ICE, EV, PHEV etc.) depending on where the studies were conducted to analyse for example EOL cars or which car brands are analysed and what features the analysed cars have. Moreover, the scope of which components of the cars are analysed for their Nd-content differs between studies, some only looking at the traction motors of EVs and HEVs, others only at Nd embedded in electrical and electronic components and a third group considering both. Four of the studies give Nd intensities for HEV with an internal combustion engine as their main driving motor, which are therefore not considered as EVs under the Roadmap to Net Zero 2050 Report. Only one study discusses the Nd intensities of different types of EVs (BEV, PHEV and PHEV) as required for the modelling in the present study (Deetman et al. 2018).

Table 8 Summary of Nd intensities of different types of cars found in the literature (PM = permanent magnet).

Source	Metric given in source	Type of car	g Nd/unit	Comment
(Månberger and Stenqvist, 2018)	PM motor for EV: 0.0038 kg Nd/kW	EV	380	assuming 100 kW for an average car
(Habib 2015)	1.14 kg PM until 2011, 1.72 kg PM from 2012 on	ICE	330.6 until 2011 498.8 from 2012	"conventional car" 29 % Nd (case study for Denmark)
	As conventional vehicle + 2 kg of magnet for the motor/generator system	EV and HEV	1118.8	31 % Nd for PM in motor (case study for Denmark)
(Widmer et al. 2015)	g Nd per car	ICE	2.4	Average midrange car (electrical and electronic components only)

(Shaw and Constantinides 2012)	250 g NdFeB magnet per standard car in 2012	ICE	75	Assuming 30 % Nd in magnet
(Deetman et al. 2018)	g Nd per car	ICE	2 – 415	Based on a literature review, (see references therein)
		HEV	118 – 995	
		PHEV	**473 – 1460**	
		BEV	**567 – 2250**	
		FCEV	**2 – 2920**	
(Ballinger et al. 2019)	g Nd/ plug in EV motor	PHEV & EV	250 - 470	Lower value - only driving motor
(Yao et al. 2021)	g Nd/unit	ICE	130	
	g Nd/unit	HEV	610	
(Sekine, Daigo, and Goto 2017)	1000 – 2000 g Magnet weight per driving motor of HEVs	HEV	230 – 480	23 – 24 % Nd in PM Lower value - only driving motor
(Cullbrand and Magnusson 2011)	g Nd/car	ICE	43.38 – 205.86	Conventional midsize car, low to high specified
	g Nd/car	HEV	531.88	Hybrid midsized car
	g Nd/car	ICE	27.60	Conventional large car, medium specified
(Zepf 2013)	g Nd/driving motor	EV	430	
(IEA 2021b)	kg Nd/PM motor	EV	250 - 500	
(Nordelöf et al. 2019)	1.26 kg PM/ 100 kW motor	EV	378	Assumption: 30 % Nd in PM
(Ciacci et al. 2019)	200-661 g/car	EV	200 - 661	
(Yang et al. 2016)	~1 kg Nd per vehicle	EV and HEV	~1000	
(Blagoeva et al. 2016)	1.5 kg PM per vehicle	EV and PHEV	450	Assuming 30 % Nd in magnet
	0.63 kg	HEV	189	

For further calculations, the values of Deetman et al. (2018) were used (marked bold in Table 8) with one change: the lower estimate for FCEVs was changed from being equal to the lower estimate for ICEs to being equal to the lower estimate of PHEVs. This was done because the FCEV will be using an electric driving motor and is therefore more similar to a PHEV than to an ICE.

3.2.2 Annually produced cars to reach Net Zero 2050

As described in the Methods section, the number of cars produced annually to reach Net Zero 2050 was modeled based on the mobility demand given in the Roadmap to Net Zero Report for two different scenarios, of car use - one with behavioural change and one without behavioural change. Since the mobility demand is only given for 2020, 2030, 2040 and 2050, the values for the remaining years were interpolated by fitting a square function.

The resulting fit for the scenario without behavioural change is good (Figure 9). On the contrary, the data points for the scenario with behavioural change cannot be fitted perfectly with a square function (Figure 10). However, since behavioural change is expected to be gradual over time, the values of the fitted curve are used for further calculations.

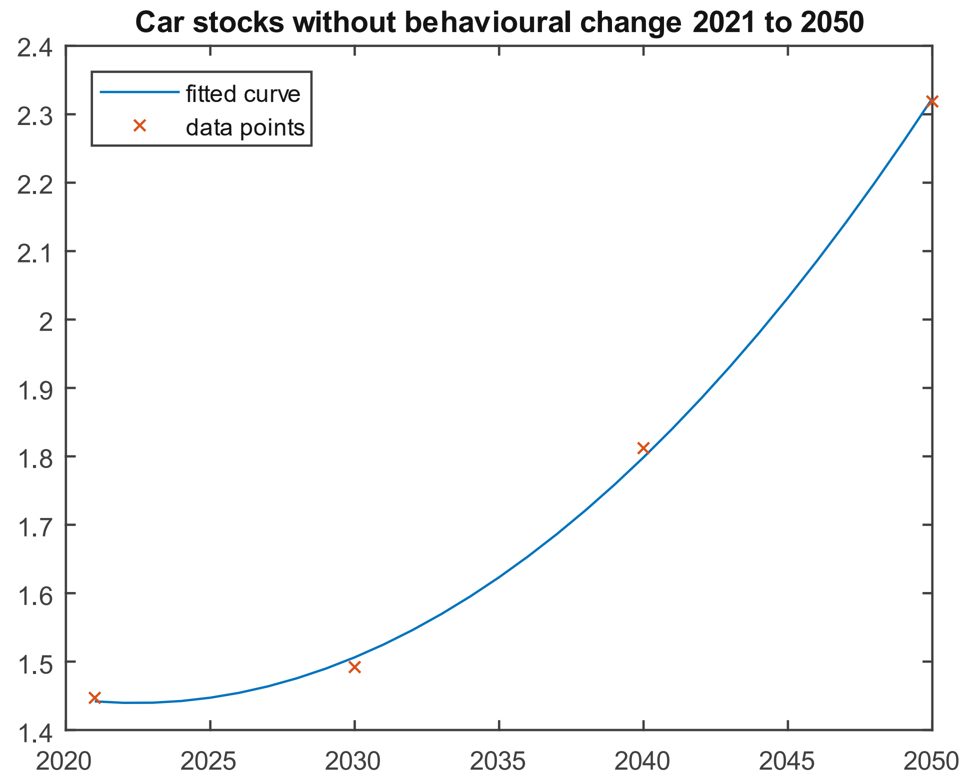


Figure 9 Development of car stocks in billion cars in a scenario without behavioural change.

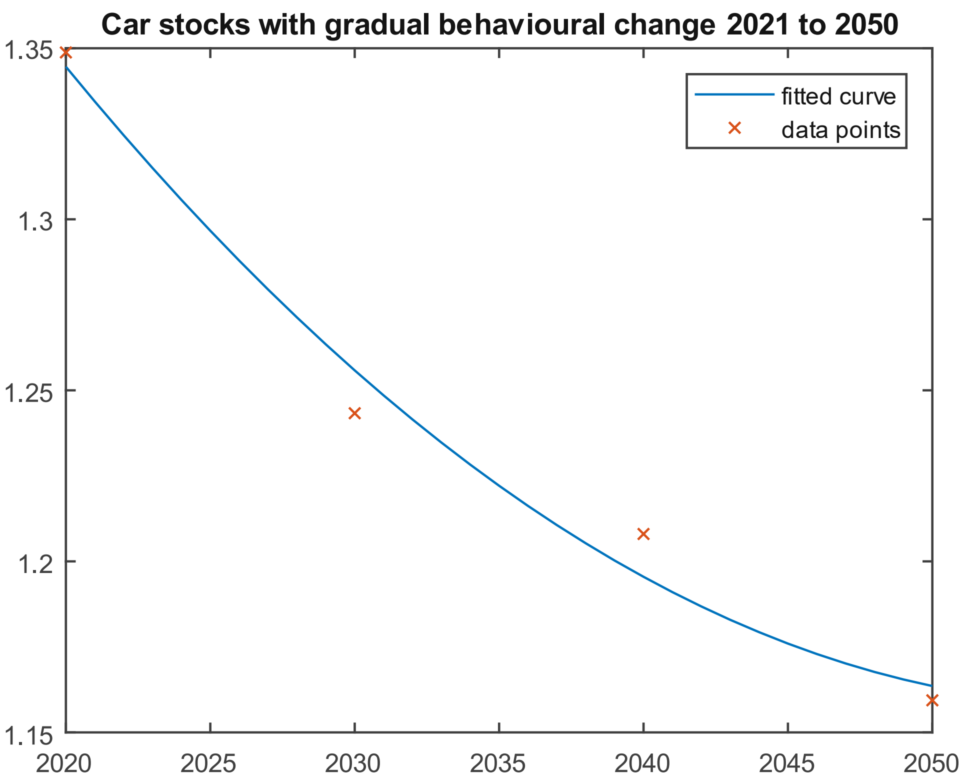


Figure 10 Development of global car stocks under the scenario with gradual behavioural change.

Based on these fitted values, the change in the stock of cars, as well as the number of cars retiring annually, and annual car sales were modeled. The results for the scenario without behavioural change is shown in Figure 11 and the results for the scenario with behavioural change in Figure 12.

In both figures, from the year 2032 onwards the graph changes from showing spikes to a smooth curve. This is due to the change in modelling approach: before 2032 a fixed lifetime was assumed to model the number of retiring cars and based on this number the annual car sales, whereas for the years after 2032, a Weibull lifetime function was used.

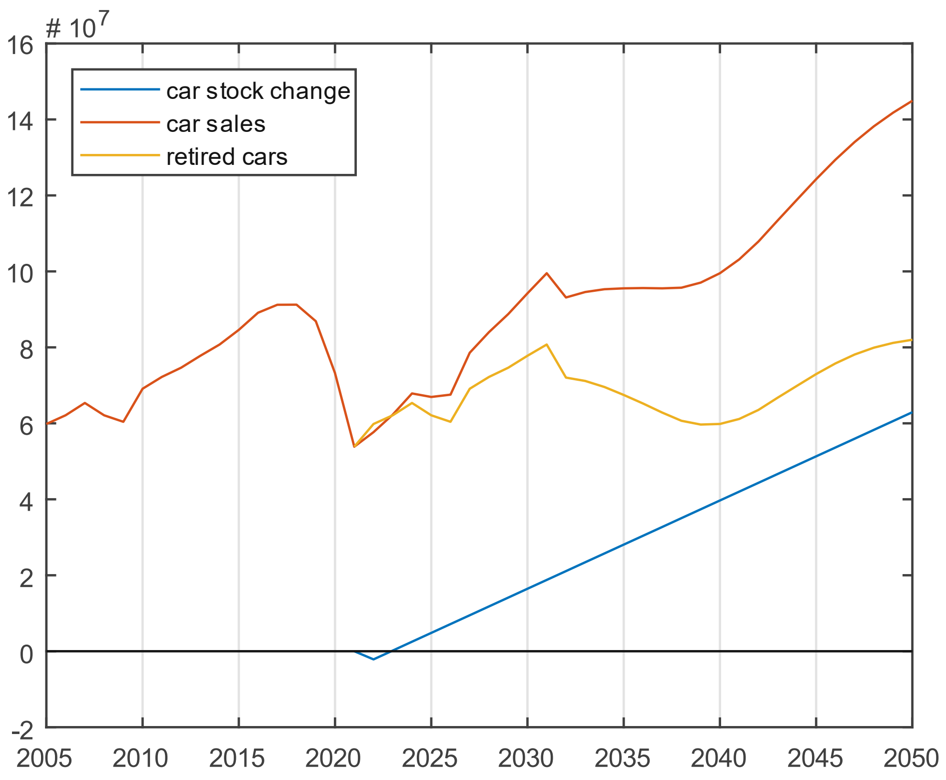


Figure 11 Global change in the stock of cars, car sales and number of retiring cars reaching their end of life in a scenario without behavioural change.

For the scenario without behavioural change, the stock of cars increases gradually after the recovery car sales due to the Covid-19 pandemic between 2020 and 2022. Around the year 2040, the number of retiring cars decreases, reflecting the decrease in car sales one lifetime of 17 years before during the Covid-19 pandemic. Also, the effect of the financial crisis of 2008 is reflected in the results with a dip in car sales around 2008 and the corresponding decrease in retiring cars around 2025. The dip in forecasted car sales for 2025 is due to the way car sales are modelled as the sum of the change in car stocks and the number of retiring cars.

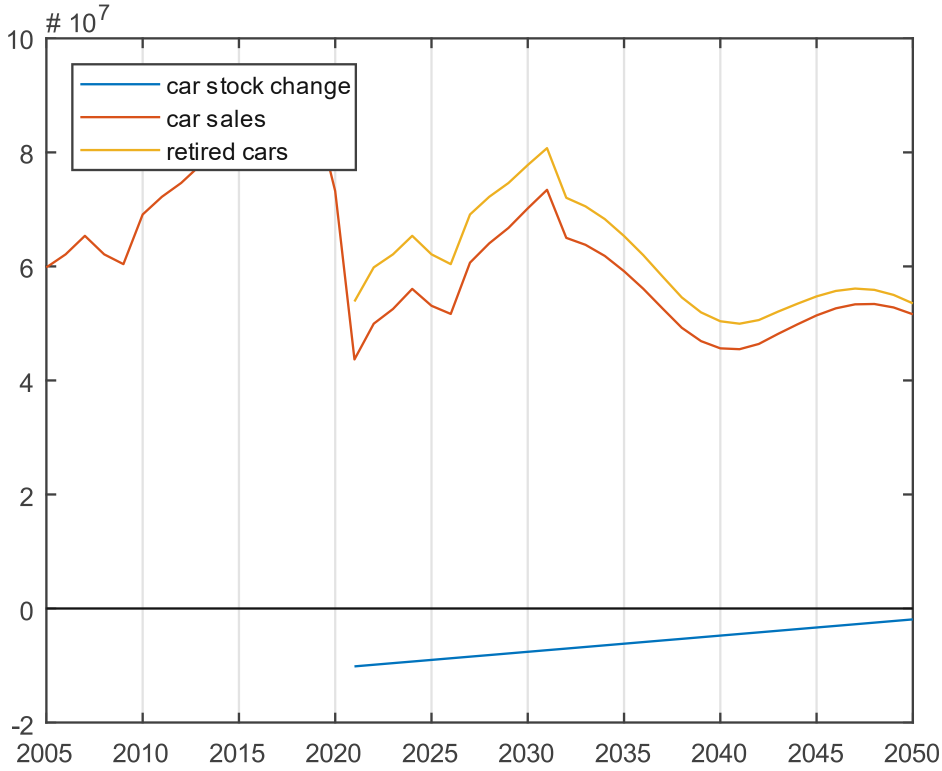


Figure 12 Global change in the stock of cars, car sales and number of retiring cars reaching their end of life in a scenario with gradual behavioural change.

In contrast to the scenario without behavioural change, where the global car stocks increase, the model reveals that behavioural change would lead to decreasing car stocks. However, the rate of the decrease diminishes over time as the global population grows. As a consequence of the decreasing car stocks, the number of cars retiring each year is larger than the number of cars being sold. As for the scenario without behavioural change, the effect of the 2008 financial crisis and the Covid-19 pandemic are reflected in the graph.

3.2.3 Annually sold EVs to reach Net Zero 2050

Using the shares of sales for BEV, PHEV and FCEV of the total car sales (given in Table 2) and the modeled annual car sales from above, the number of all EVs sold annually was calculated.

If it is compared to the historic EV sales, it can be seen that the strong increase in EV sales holds on in 2021, despite of the strong decrease in total car sales due to the pandemic (IEA 2020). The model results in comparison to historic EV sales numbers from IEA (2020) are shown in Table 9. The car sales in the scenario with gradual behavioural change are only about half the car sales in the scenario without behavioural change in 2040 and even less in 2050.

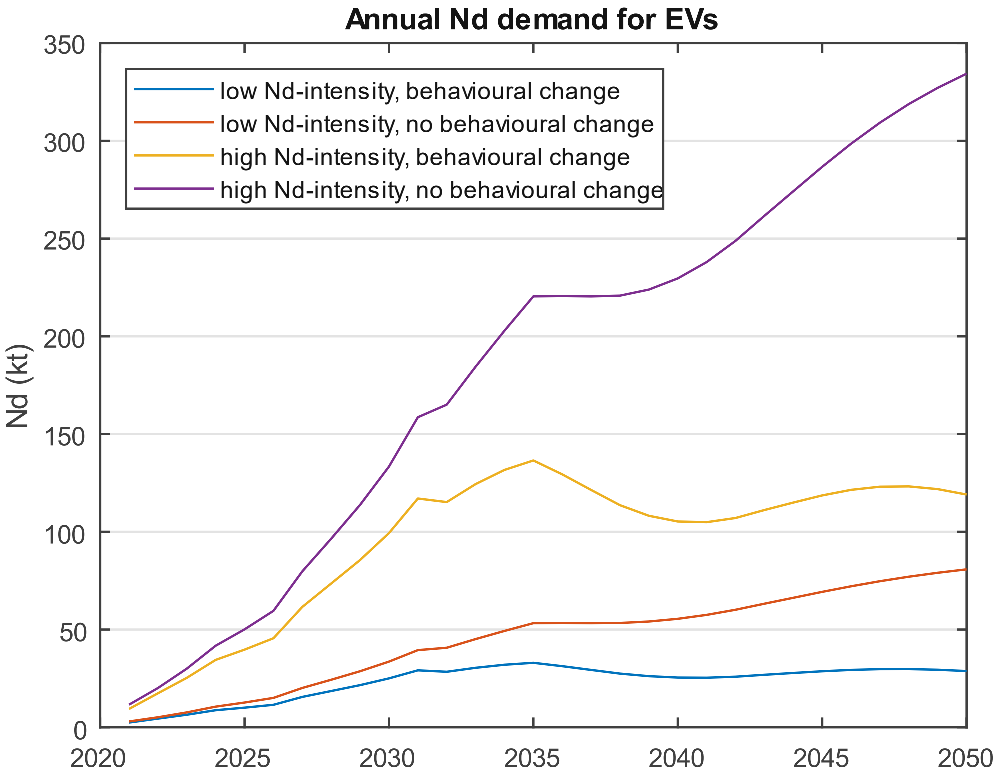
Table 9 Comparison of historic EV sales (IEA 2020) *to modeled EV sales under a scenario with and without behavioural change.*

	Historic EV sales (IEA 2020)	EV sales with gradual behavioural change	EV sales without behavioural change
2015	540 000	-	-
2016	750 000	-	-
2017	1 140 000	-	-
2018	1 950 000	-	-
2019	2 040 000	-	-
2020	3 070 000	-	-
2021	-	4 398 426	5 420 898
2030	-	45 267 981	60 776 696
2035	-	59 111 027	95 462 668
2040	-	45 587 871	99 443 877
2050	-	51 561 891	144 811 383

3.2.4 Nd demand for EVs to reach Net Zero 2050

The demand for Nd to build the EVs required for the mobility demand according to the Net Zero 2050 Report was also modeled under the two scenarios without behavioural change and with gradual behavioural change. Moreover, a lower and upper estimate of the Nd-intensity for each of the EV sub-technologies (BEV, PHEV, FCEV) was used to get a minimum and maximum expected demand for Nd.

The modelling results for Nd demand are summed up in Table 11 and visualized in Figure 13. The difference between the scenarios with and without behavioural change is smaller than the difference resulting from using the high and low estimate for Nd intensity of EVs. Under the scenario with behavioural change, the Nd demand for EVs is at a roughly constant level from 2035 on, whereas it increases continuously for the scenario without behavioural change as seen in Figure 13.



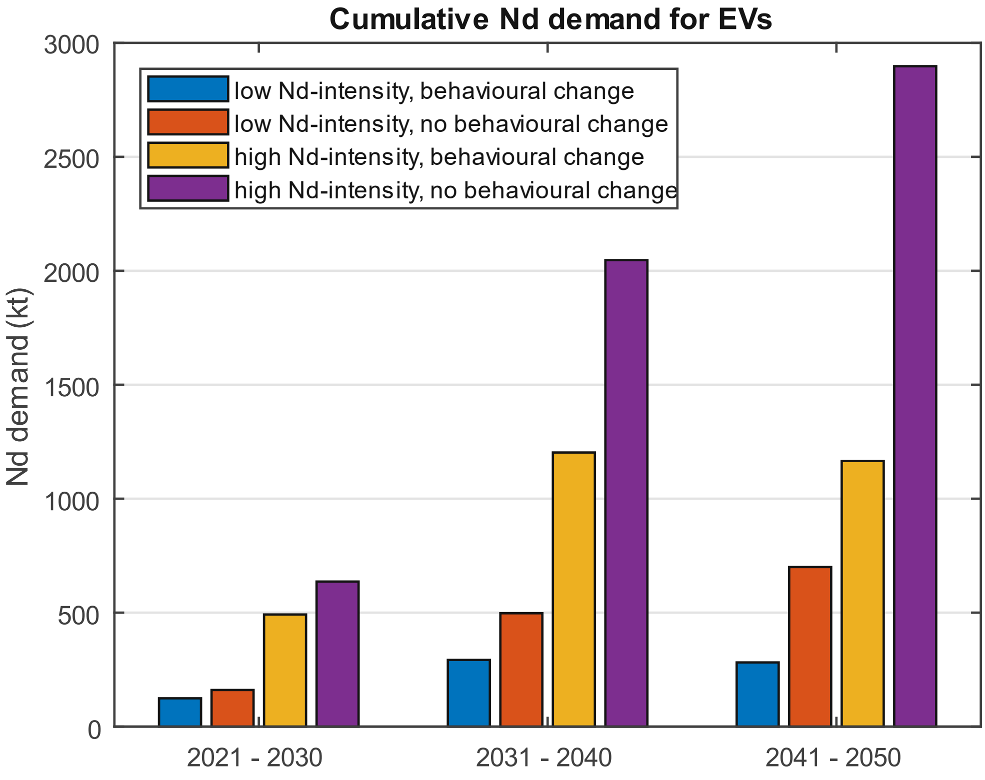


Figure 13 Annual Nd demand for EVs under 4 different scenarios, and cumulative Nd-demand over 10-year periods (2021 – 2030, 2031 – 2040, 2041 – 2050).

If the modeled results are compared to the published data by IEA (2021a), it is interesting to note, that the modeled results are consistently higher, and the extreme model scenario without behavioural change and with a high Nd-intensity estimate is even a magnitude larger. This firstly is due to the fact that IEA (2021a) only account for the Nd in the [traction] motors of the EVs and secondly due to the much lower Nd intensity of 250 – 500 g per motor reported. Moreover, the used literature sources of IEA (2021a) including papers on the substitution of Nd in EV motors, suggest that decreasing Nd intensities due to technological advance were accounted for. This study assumes that all EVs use permanent magnets in their motors, uses higher Nd intensities (see Table 3) and does not account for possible changes of the Nd intensity of EVs over time.

Table 10 Comparison of the model results for the annual demand of Nd (in t) for EVs with literature data from IEA (2021a).

	2020	2030	2040
IEA stated policy scenario (EV)	1 801	8 623	10 939
IEA sustainable development scenario (EV)	1 801	18 374	27 709
With behavioural change, low Nd-intensity	2 408	25 014	25 431
Without behavioural change, low Nd-intensity	2 968	33 584	55 475
With behavioural change, high Nd-intensity	9 372	99 335	105 264
Without behavioural change, high Nd-estimate	11 551	133 368	229 620

Table 11 Annual Nd demand (in t) for different types of EVs under the 2 different scenarios (with and without behavioural change) and for a lower and higher estimate for Nd intensity of BEV, PHEV and FCEV.

low Nd intensity	2021	2022	2023	2024	2025	2026	2027	2028	2029	2030
BEV with behavioural change	1 977	3 727	5 462	7 476	8 640	9 925	13 434	16 065	18 705	21 727
PHEV with behavioural change	368	558	730	933	1 030	1 144	1 509	1 769	2 027	2 324
FCEV with behavioural change	64	141	220	311	367	427	584	704	825	963
BEV without behavioural change	2 436	4 304	6 478	9 050	10 893	12 976	17 404	21 074	24 871	29 171
PHEV without behavioural change	453	644	866	1 130	1 298	1 495	1 955	2 321	2 695	3 120
FCEV without behavioural change	78	163	260	376	462	559	757	923	1 097	1 293

low Nd intensity	2031	2032	2033	2034	2035	2036	2037	2038	2039	2040
BEV with behavioural change	25 697	25 374	27 472	29 132	30 256	28 681	26 913	25 181	23 984	23 334
PHEV with behavioural change	1 974	1 343	921	508	118	111	105	98	93	91
FCEV with behavioural change	1 452	1 679	2 033	2 346	2 602	2 467	2 315	2 166	2 063	2 007
BEV without behavioural change	34 825	36 351	40 731	44 895	48 862	48 902	48 862	48 949	49 633	50 900
PHEV without behavioural change	2 675	1 924	1 365	783	190	190	190	190	193	198
FCEV without behavioural change	1 968	2 405	3 015	3 615	4 203	4 206	4 203	4 210	4 269	4 378

low Nd intensity	2041	2042	2043	2044	2045	2046	2047	2048	2049	2050
BEV with behavioural change	23 259	23 730	24 635	25 483	26 291	26 925	27 283	27 314	27 004	26 392
PHEV with behavioural change	90	92	96	99	102	105	106	106	105	103
FCEV with behavioural change	2 001	2 041	2 119	2 192	2 261	2 316	2 347	2 349	2 323	2 270
BEV without behavioural change	52 756	55 161	58 000	60 784	63 553	66 176	68 564	70 677	72 513	74 121
PHEV without behavioural change	205	214	225	236	247	257	266	275	282	288
FCEV without behavioural change	4 538	4 744	4 989	5 228	5 466	5 692	5 897	6 079	6 237	6 375

high Nd intensity	2021	2022	2023	2024	2025	2026	2027	2028	2029	2030
BEV with behavioural change	7 844	14 791	21 676	29 665	34 287	39384	53 308	63 752	74 228	86 220
PHEV with behavioural change	1 135	1 721	2 255	2 881	3 178	3530	4 658	5 461	6 257	7 173
FCEV with behavioural change	393	869	1 356	1 918	2 264	2637	3 606	4 346	5 091	5 943
BEV without behavioural change	9 667	17 079	25 706	35 913	43 227	51494	69 062	83 625	98 696	115 758
PHEV without behavioural change	1 399	1 987	2 674	3 488	4 007	4616	6 035	7 163	8 320	9 630
FCEV without behavioural change	484	1 004	1 608	2 322	2 854	3448	4 672	5 701	6 770	7 979

high Nd intensity	2031	2032	2033	2034	2035	2036	2037	2038	2039	2040
BEV with behavioural change	101 972	100 689	109 015	115 601	120 062	113813	106 796	99 925	95 173	92 595
PHEV with behavioural change	6 094	4 146	2 842	1 567	363	344	323	302	288	280
FCEV with behavioural change	8 963	10 364	12 553	14 482	16 065	15229	14 290	13 371	12 735	12 390
BEV without behavioural change	138 196	144 250	161 631	178 155	193 897	194057	193 896	194 241	196 955	201 983
PHEV without behavioural change	8 258	5 939	4 214	2 416	586	586	586	587	595	610
FCEV without behavioural change	12 146	14 848	18 612	22 319	25 945	25966	25 944	25 991	26 354	27 027

high Nd intensity	2041	2042	2043	2044	2045	2046	2047	2048	2049	2050
BEV with behavioural change	92 297	94 167	97 759	101 121	104 330	106844	108 265	108 388	107 159	104 729
PHEV with behavioural change	279	285	295	306	315	323	327	327	324	316
FCEV with behavioural change	12 350	12 600	13 081	13 531	13 960	14296	14 487	14 503	14 339	14 013
BEV without behavioural change	209 348	218 892	230 160	241 208	252 196	262605	272 080	280 464	287 751	294 130
PHEV without behavioural change	633	661	695	729	762	793	822	847	869	889
FCEV without behavioural change	28 012	29 289	30 797	32 275	33 745	35138	36 406	37 528	38 503	39 356

3.3 Nd Reserves and production capacities

The official world production of rare earths in rare earth oxide equivalents was between 226 kt to 240 kt in 2020 which corresponds to 31 kt to 33 kt Nd. Illegal mining in China, which is not accounted for in the official figures, plays a very important role as it contributed more than 30 % of the total world production in 2017 (Yao et al. 2021; Reichl and Schatz 2022) and the upper estimate of Geng et al. (2020) equals to nearly 90 % of the official global production of Nd (Reichl and Schatz 2022) (Table 12). Moreover, illegal mining in China showed an average growth rate of 10 % between 2000 and 2017 (Yao et al. 2021).

Table 12 Official world production of rare earth elements expressed on rare earth oxide equivalents (REO eq.) according to different sources (Reichl and Schatz 2022; Idoine et al. 2022; U.S. Geological Survey 2022)*, calculated Nd production, and Nd production from illegal mining in China.*

	year	REO eq. production (in t/year)	Nd production (in t/year)
International Organizing Committee for the World Mining Congresses "World Mining Data"	2020	225 277	30 807
British Geological Survey "World Mineral Production"	2020	232 039	31 732
U.S. Gelogical Survey "Mineral Commodity Summaries"	2020	240 000	32 821
U.S. Gelogical Survey "Mineral Commodity Summaries"	2021*	280 000	38 291
illegal mining in China (Geng et al., 2020)	2016		12 300 - 17 000
illegal mining in China (Yao et al., 2021)	2017		11 300

Official REO production increased by 73.52 % comparing 2016 to 2020 (Reichl and Schatz 2022), which is even more than during the previous 4-year period from 2015 to 2019 where production increased by 62.25 % (Reichl and Schatz 2021).

Reserves of REOs are 120 Mt (U.S. Geological Survey 2022) which corresponds to 19.2 Mt Nd-oxides assuming 16 % Nd oxides per REO or 17.3 Mt Nd.

This shows that annual Nd production in 2021, even considering the high estimate for illegal mining in China, was only 0,3 % of the known reserves. This finding is in line with other studies that also found no risk production exceeding reserves by 2050 under different scenarios for demand growth (Månberger and Stenqvist 2018; Habib 2015; Blagoeva et al. 2016).

The average annual growth rate of official REO production between 2011 and 2020 was 9.7 % (Reichl, Schatz, and Zsak 2017; Reichl and Schatz 2022). If this growth rate is applied to the total Nd production of 2021 (official mining according to (U.S. Geological Survey 2022) plus a medium estimate of 15 kt illegal mining (Geng et al. 2020)), Nd production reaches 123 kt in 2030, 309 kt in 2040 and 781 kt in 2050 (Figure 14).

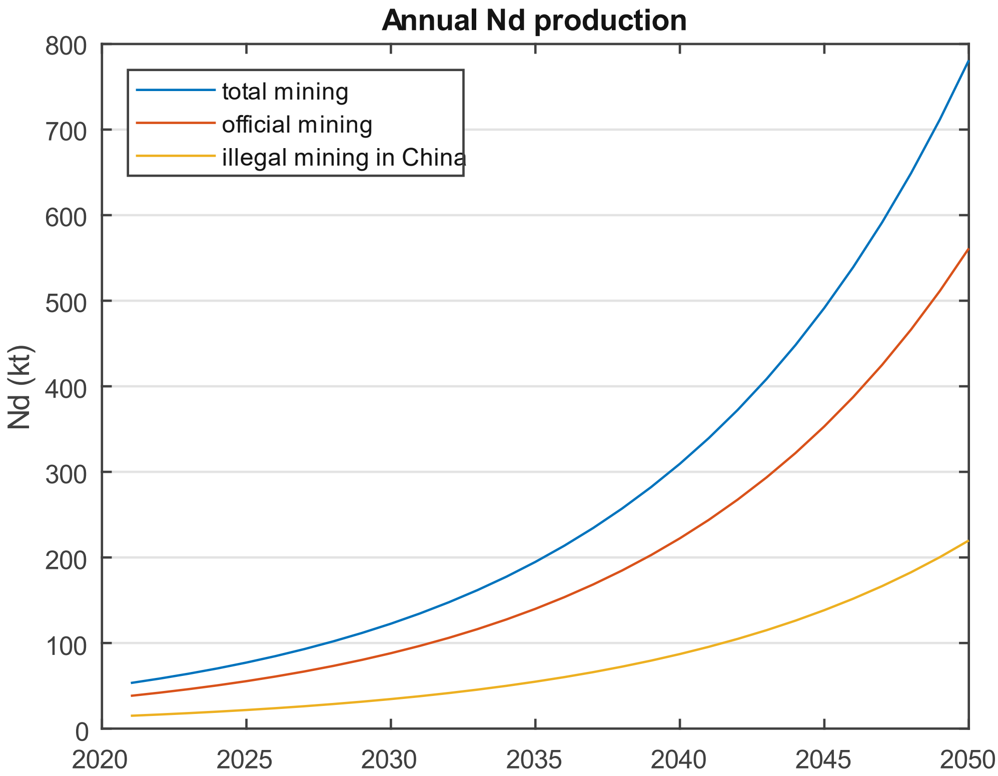


Figure 14 Annual Nd production through official mining and the contribution of illegal mining in China, assuming 9.7% annual increase in production.

The cumulative amount of Nd mined each decade is shown in Figure 15.

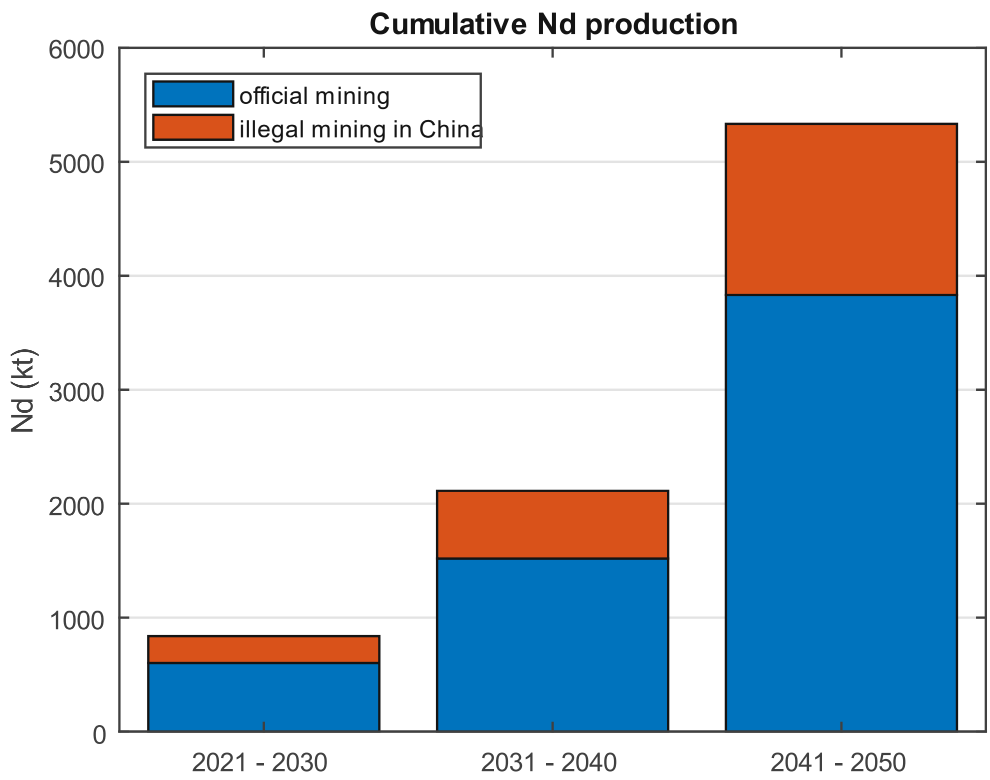


Figure 15 Amount of Nd mined each decade from 2021 to 2050.

3.4 Nd Recycling Potential

To calculate the potential contribution of secondary Nd to meet the annual demand, firstly the annually released Nd stocks from wind retiring turbines and EVs were calculated before applying transfer coefficients for the efficiency of disassembly and recycling.

The efficiencies of different technologies and steps in the recycling process of NdFeB magnets reported in the literature are listed in the following table. All the described technologies are currently only proven on a lab scale, as only very limited industrial scale NdFeB magnet recycling exists (Goonan 2011; Shaw and Constantinides 2012; Ciacci et al. 2019) and the current Nd recycling rate is below 1 % (Yao et al. 2021). In the following calculations, the disassembly and recycling efficiency of Deng and Ge (2020) were used (marked bold in Table 13).

Table 13 Literature review of the efficiency of different recycling technologies for NdFeB magnets.

Source	Recycling technology	Efficiency	Comment
(Kumari et al. 2018)	Hydrochloric acid leaching	98 %	
(Chowdhury et al. 2021)	Copper nitrate leaching	~97 %	Economically feasible technology
(Yang et al. 2016)	Hydrometallurgical with oxalic precipitation	82 %	Total REE recovery rate from shredding to oxalic precipitation
	Pyrometallurgical (sulfation roasting and waterleaching)	>95 %	
	Molten Slag extraction	99 %	Highly effective for magnet scarp like shredded HDD
	Selective leaching with roasting	70 %	
(Habib and Wenzel 2014)	Overall recycling rate	90 % for wind turbines 70 % for EVs	Assumption for total REE recovery with 100 % collection rate
(München, Bernardes, and Veit 2018)	Sulphuric acid leaching	≤90.3 %	
(Pietrantonio et al. 2021)	Nitric acid leaching and oxalate precipitation of REE	90 %	Suitable for EOL wind turbine magnets
(Schulze and Buchert 2016)	Overall efficiency of REE recovery after	60 %	Assumption

	extraction of NdFeB magnet		
(Zhang et al. 2020)	Selective leaching (different solvents and pretreatment like roasting)	>87 %	Review of different literature sources, leaching efficiency only
	Complete leaching with sulfuric acid	>99.4 %	
	Bioleaching	91 %	
	REE separation via precipitation (different reagents)	96.7 – 99 %	Review of different literature sources, recovery efficiency (after leaching)
	REE separation via solvent extraction (different reagents)	95 - 99.99 %	
(Dupont and Binnemans 2015)	Combined leaching/extraction with ionic liquid	>99 %	
(Deng and Ge 2020)	**Disassembly rate**	**90 %**	**Efficiency of disassembly**
	Recycling rate	**90 %**	**Efficiency of recycling process**

3.4.1 Nd Recycling Potential from EOL EVs

To calculate the amount of Nd that is able to be recovered and reintroduced to the market again, it was assumed that 30% of EOL cars have unknown whereabouts and do not end up in disassembly and recycling (Dworak, Rechberger, and Fellner 2022). The efficiency rate of disassembly as well as the efficiency rate of the recycling process were assumed to be 90 % each (Deng and Ge 2020).

The results for the recycling potential are shown in Table 15.

Table 16 shows the percentage of the Nd demand for EVs that could potentially be covered from Nd recovered from EOL EVs each year. The scenarios with high or low Nd intensity are approximately the same. On the other hand, behavioural change makes a difference: in the scenarios with behavioural change, the percentage of Nd demand that can potentially be covered by recycled Nd is about twice as high from 2040 on as compared to the scenarios without behavioural change. In 2040 ~7 % and ~14 % and in 2050 ~31 % and ~60 % of Nd demand could be met by recycling respectively for scenarios without and with behavioural change.

The amount of Nd that can potentially be recovered each decade under each scenario is visualized in Figure 16. The same observation as for the demand for Nd applies as described in Chapter 3.2.4.

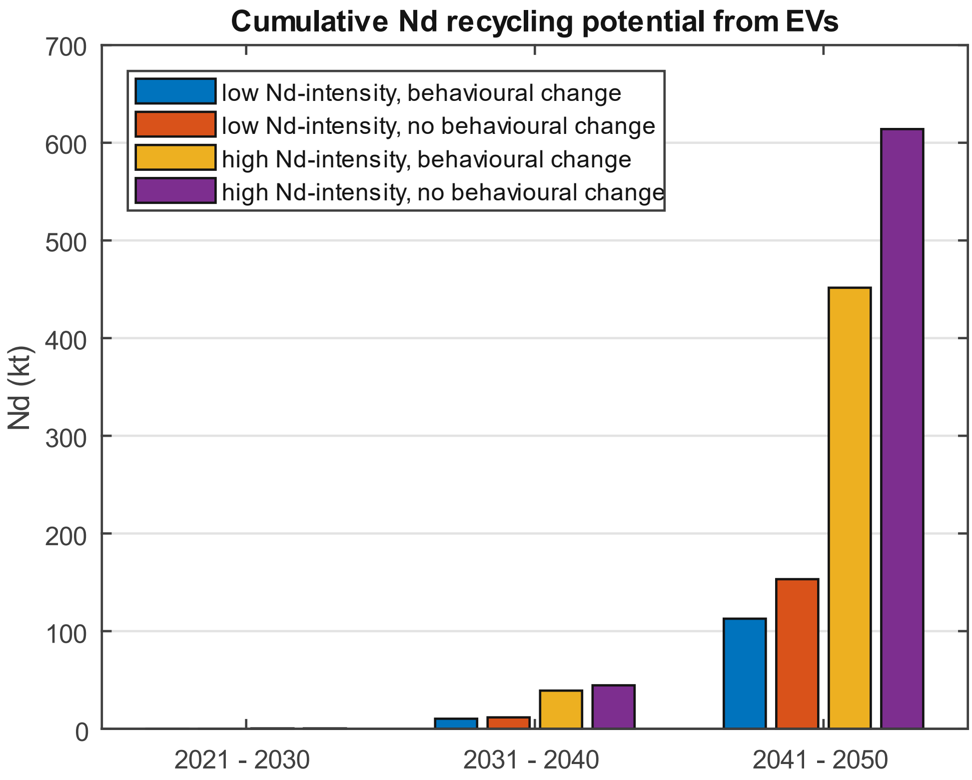


Figure 16 Cumulative amount of Nd that could potentially be gained from recycling of EOL EVs each decade.

Table 14 Released amounts of Nd (in t/year) via end-of-life EVs.

	2027	2028	2029	2030	2031	2032	2033	2034	2035	2036	2037
All scenarios	15	96	223	386	555	962	1 332	1 973	3 337	3 405	5 358

	2038	2039	2040	2041	2042	2043	2044	2045	2046	2047	2048	2049	2050
with behavioural change, low Nd intensity	2 408	4 426	6 413	8 720	10 037	11 496	15 527	18 539	21 557	25 014	29 123	28 395	30 426
without behavioural change, low Nd intensity	2 968	5 110	7 605	10 556	12 654	15 030	20 115	24 318	28 663	33 584	39 468	40 680	45 111
with behavioural change, high Nd-intensity	9 372	17 382	25 287	34 464	39 728	45 552	61 573	73 559	85 576	99 335	117 029	115 198	124 410
without behavioural change, high Nd-intensity	11 551	20 070	29 988	41 723	50 088	59 557	79 769	96 489	113 785	133 368	158 600	165 037	184 458

Table 15 Recycling potential of Nd from EVs: Potential amount of recycled/reused Nd (in t(year) from EVs reaching the market.

	2027	2028	2029	2030	2031	2032	2033	2034	2035	2036	2037
with behavioural change, low Nd intensity	3	17	35	62	90	157	217	327	556	576	885
without behavioural change, low Nd intensity	8	54	126	219	315	546	755	1 118	1 892	1 931	3 038

	2027	2028	2029	2030	2031	2032	2033	2034	2035	2036	2037
with behavioural change, high Nd-intensity	2	15	31	55	80	139	193	290	494	512	787
without behavioural change, high Nd-intensity	7	48	112	194	280	485	671	994	1 682	1 716	2 700

	2038	2039	2040	2041	2042	2043	2044	2045	2046	2047	2048	2049	2050
with behavioural change, low Nd intensity	1 365	2 509	3 636	4 944	5 691	6 518	8 804	10 511	12 223	14 183	16 513	16 100	17 252
without behavioural change, low Nd intensity	1 683	2 898	4 312	5 985	7 175	8 522	11 405	13 788	16 252	19 042	22 379	23 066	25 578
with behavioural change, high Nd-intensity	5 314	9 856	14 338	19 541	22 526	25 828	34 912	41 708	48 522	56 323	66 355	65 317	70 541
without behavioural change, high Nd-intensity	6 549	11 380	17 003	23 657	28 400	33 769	45 229	54 709	64 516	75 619	89 926	93 576	104 588

Table 16 Percentage of the demand for Nd in EVs that could potentially be covered by recovered Nd from end-of-life EVs.

	2027	2028	2029	2030	2031	2032	2033	2034	2035	2036	2037
with behavioural change, low Nd intensity	0.02%	0.09%	0.16%	0.25%	0.31%	0.55%	0.71%	1.02%	1.69%	1.84%	3.02%
without behavioural change, low Nd intensity	0.04%	0.22%	0.44%	0.65%	0.80%	1.34%	1.67%	2.27%	3.55%	3.62%	5.70%
with behavioural change, high Nd-intensity	0.00%	0.02%	0.04%	0.06%	0.07%	0.12%	0.16%	0.22%	0.36%	0.40%	0.65%
without behavioural change, high Nd-intensity	0.01%	0.05%	0.10%	0.15%	0.18%	0.29%	0.36%	0.49%	0.76%	0.78%	1.23%

	2038	2039	2040	2041	2042	2043	2044	2045	2046	2047	2048	2049	2050
with behavioural change, low Nd intensity	4.98%	9.60%	14.30%	19.50%	22.00%	24.28%	31.70%	36.68%	41.65%	47.70%	55.47%	54.70%	59.98%
without behavioural change, low Nd intensity	3.15%	5.36%	7.77%	10.41%	11.93%	13.48%	17.22%	19.91%	22.53%	25.48%	29.05%	29.19%	31.66%

with behavioural change, high Nd-intensity	4.68%	9.11%	13.62%	18.62%	21.04%	23.24%	30.37%	35.17%	39.95%	45.76%	53.85%	53.62%	59.25%
without behavioural change, high Nd-intensity	2.97%	5.08%	7.41%	9.94%	11.41%	12.91%	16.49%	19.08%	21.61%	24.45%	28.20%	28.61%	31.28%

3.4.2 Nd Recycling Potential from EOL Wind Turbines

The modelling results for the amounts of Nd released from stocks of wind turbines are shown in

Figure 17. For offshore wind turbines, due to their longer lifetime and later introduction, the released amounts of Nd are negligible until 2035. Depending on the scenario, they reach between 4 kt (LDS) and over 7 kt (IEA baseline). Amounts of Nd released from onshore wind turbines are much larger and reach nearly 2 kt in 2035 and 5.5 kt (IEA constrained REE) to 11 kt (HDS) in 2050.

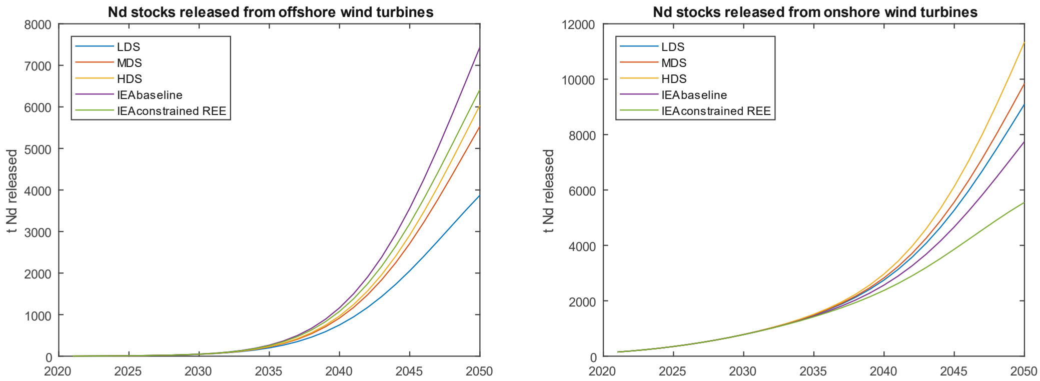


Figure 17 Amount of Nd released from stocks of offshore and onshore wind turbines each year.

To calculate the amount of Nd that is able to be recovered and put on the market again, it was assumed that all of the EOL wind turbines are disassembled for recycling or reuse (Deng and Ge 2020). The efficiency rate of disassembly as well as the efficiency rate of the recycling process were assumed to be 90 % each (Deng and Ge 2020). The results are shown in Table 17. Moreover, the results are visualized in Figure 18 for each decade cumulatively. The same observation as for the demand for Nd apply as described in Chapter 3.1.4.

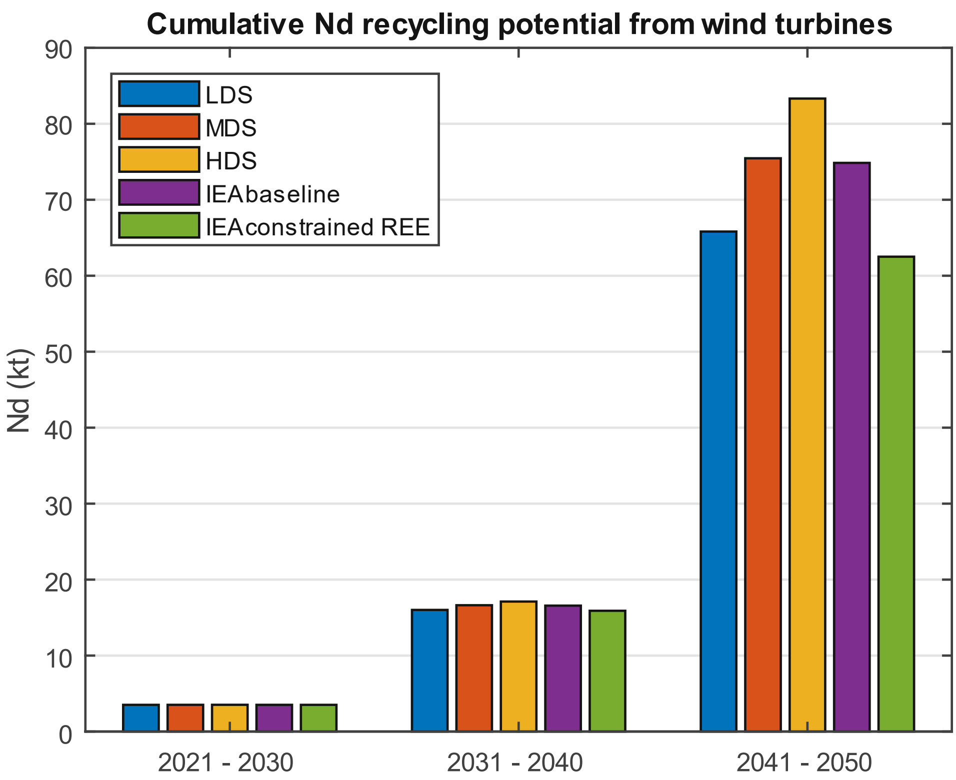


Figure 18 Cumulative amount of Nd that could potentially be gained from recycling of EOL wind turbines each decade.

The percentage of the demand that could potentially be covered by Nd from recycled EOL wind turbines is shown in Table 18. The analysis shows that by 2040, 10 % (HDS) to 15 % (IEA baseline) or even ~30 % under the IEA constrained REE scenario could be met by recycling of Nd from wind turbines for onshore and offshore each and by 2050 ~60 % to over 100 % for onshore, ~37 – 47 % for offshore, and ~51 – 68 % of the total Nd demand for wind turbines.

Table 17 Recycling potential of Nd from wind turbines: Potential amount of recycled/reused Nd (in t/year) from wind turbines reaching the market.

	2021	2022	2023	2024	2025	2026	2027	2028	2029	2030
onshore LDS	122	153	190	233	283	339	402	472	549	634
onshore MDS	122	153	190	233	283	339	402	472	549	635
onshore HDS	122	153	190	233	283	339	402	472	550	636
onshore IEA baseline	122	153	190	233	283	339	401	471	547	631
onshore IEA constrained REE	122	153	190	233	283	339	401	471	547	630
offshore LDS	3	4	5	7	9	12	16	21	28	37
offshore MDS	3	4	5	7	9	12	16	21	28	38
offshore HDS	3	4	5	7	9	12	16	21	28	38
offshore IEA baseline	3	4	5	7	9	12	16	22	29	41
offshore IEA constrained REE	3	4	5	7	9	12	16	21	29	40

	2031	2032	2033	2034	2035	2036	2037	2038	2039	2040
onshore LDS	727	829	941	1 064	1 201	1 355	1 529	1 729	1 961	2 229
onshore MDS	728	831	945	1 070	1 211	1 370	1 552	1 762	2 006	2 292
onshore HDS	730	835	951	1 081	1 228	1 396	1 590	1 818	2 087	2 405
onshore IEA baseline	722	821	929	1 045	1 173	1 314	1 471	1 648	1 849	2 080
onshore IEA constrained REE	720	817	921	1 033	1 152	1 281	1 420	1 572	1 740	1 924
offshore LDS	49	67	90	121	162	215	284	371	478	609
offshore MDS	52	71	97	133	181	245	329	437	574	743
offshore HDS	52	72	99	136	187	254	343	458	603	785

offshore IEA baseline	56	79	111	155	215	296	404	543	721	943
offshore IEA constrained REE	56	77	108	150	206	282	382	510	672	873

	2041	2042	2043	2044	2045	2046	2047	2048	2049	2050
onshore LDS	2 539	2 896	3 303	3 761	4 271	4 827	5 424	6 054	6 706	7 370
onshore MDS	2 624	3 009	3 451	3 951	4 509	5 123	5 786	6 490	7 224	7 975
onshore HDS	2 779	3 218	3 726	4 308	4 964	5 693	6 490	7 347	8 251	9 190
onshore IEA baseline	2 343	2 644	2 983	3 363	3 781	4 235	4 720	5 228	5 750	6 277
onshore IEA constrained REE	2 128	2 351	2 593	2 853	3 127	3 409	3 695	3 976	4 247	4 499
offshore LDS	766	950	1 162	1 401	1 664	1 946	2 243	2 546	2 847	3 137
offshore MDS	950	1 197	1 487	1 821	2 196	2 609	3 054	3 522	4 001	4 481
offshore HDS	1 007	1 273	1 587	1 950	2 359	2 813	3 302	3 820	4 354	4 892
offshore IEA baseline	1 215	1 544	1 931	2 378	2 885	3 445	4 052	4 695	5 358	6 026
offshore IEA constrained REE	1 118	1 411	1 753	2 145	2 584	3 065	3 579	4 115	4 660	5 199

Table 18 Percentage of the Nd demand for wind turbines that could potentially be covered by recycled Nd from EOL wind turbines.

	2021	2022	2023	2024	2025	2026	2027	2028	2029	2030
onshore LDS	4.16%	3.37%	3.16%	3.16%	3.29%	3.50%	3.78%	4.11%	4.52%	4.99%
onshore MDS	2.23%	5.12%	4.05%	3.71%	3.65%	3.72%	3.89%	4.12%	4.42%	4.53%
onshore HDS	2.23%	4.89%	3.82%	3.45%	3.34%	3.36%	3.47%	3.63%	3.85%	3.86%
onshore IEA baseline	2.48%	5.78%	4.66%	4.35%	4.35%	4.51%	4.80%	5.17%	5.64%	5.99%
onshore IEA constrained REE	2.48%	5.99%	5.01%	4.86%	5.06%	5.50%	6.13%	6.96%	8.02%	9.65%

offshore LDS	0.22%	0.19%	0.19%	0.21%	0.23%	0.27%	0.33%	0.40%	0.49%	0.63%
offshore MDS	0.20%	0.17%	0.16%	0.17%	0.18%	0.20%	0.23%	0.27%	0.33%	0.40%
offshore HDS	0.19%	0.16%	0.15%	0.16%	0.17%	0.19%	0.22%	0.25%	0.30%	0.36%
offshore IEA baseline	0.15%	0.13%	0.12%	0.13%	0.14%	0.15%	0.18%	0.21%	0.25%	0.31%
offshore IEA constrained REE	0.15%	0.13%	0.13%	0.14%	0.15%	0.17%	0.20%	0.24%	0.30%	0.37%

	2031	2032	2033	2034	2035	2036	2037	2038	2039	2040
onshore LDS	5.32%	5.72%	6.18%	6.73%	7.38%	8.15%	9.08%	10.21%	11.59%	13.28%
onshore MDS	4.82%	5.17%	5.58%	6.07%	6.65%	7.35%	8.19%	9.22%	10.48%	12.04%
onshore HDS	4.07%	4.32%	4.63%	5.00%	5.45%	6.00%	6.67%	7.49%	8.51%	9.78%
onshore IEA baseline	6.40%	6.87%	7.43%	8.07%	8.83%	9.71%	10.76%	12.02%	13.55%	15.40%
onshore IEA constrained REE	10.55%	11.61%	12.83%	14.25%	15.90%	17.84%	20.12%	22.84%	26.11%	30.05%
offshore LDS	0.85%	1.15%	1.57%	2.12%	2.85%	3.80%	5.02%	6.55%	8.43%	13.28%
offshore MDS	0.55%	0.76%	1.04%	1.43%	1.96%	2.66%	3.56%	4.72%	6.17%	12.04%
offshore HDS	0.50%	0.69%	0.96%	1.32%	1.81%	2.47%	3.33%	4.43%	5.82%	9.78%
offshore IEA baseline	0.44%	0.61%	0.86%	1.21%	1.68%	2.31%	3.13%	4.20%	5.53%	15.40%
offshore IEA constrained REE	0.52%	0.73%	1.03%	1.45%	2.02%	2.78%	3.79%	5.09%	6.73%	30.05%

	2041	2042	2043	2044	2045	2046	2047	2048	2049	2050
onshore LDS	15.35%	17.89%	20.99%	24.78%	29.42%	35.13%	42.27%	51.40%	63.51%	80.55%
onshore MDS	13.95%	16.30%	19.18%	22.71%	27.04%	32.39%	39.08%	47.64%	59.01%	75.02%
onshore HDS	11.35%	13.29%	15.67%	18.60%	22.20%	26.66%	32.25%	39.42%	48.95%	62.39%
onshore IEA baseline	17.66%	20.41%	23.76%	27.84%	32.82%	38.95%	46.60%	56.37%	69.34%	87.59%
onshore IEA constrained REE	33.97%	38.63%	44.16%	50.73%	58.56%	67.97%	79.44%	93.79%	112.52%	138.52%

offshore LDS	13.54%	16.66%	20.15%	23.94%	27.93%	32.00%	36.00%	39.79%	43.23%	46.23%
offshore MDS	10.07%	12.54%	15.35%	18.45%	21.78%	25.25%	28.75%	32.16%	35.37%	38.29%
offshore HDS	9.56%	11.95%	14.68%	17.70%	20.97%	24.39%	27.86%	31.27%	34.50%	37.46%
offshore IEA baseline	9.17%	11.50%	14.18%	17.15%	20.36%	23.73%	27.15%	30.51%	33.71%	36.65%
offshore IEA constrained REE	11.24%	14.19%	17.59%	21.41%	25.57%	29.98%	34.51%	39.02%	43.36%	47.41%

4. Discussion

In this section, the results are discussed in the light of the existing literature and interpreted to derive conclusions. In the first sub-chapter, the plausibility of the results is discussed and the findings for Nd demand in wind turbines and EVs compared to each other. The second sub-chapter briefly discusses the effect of technological advance and the substitution of Nd or Nd-based technologies on the demand. Next, arguments are presented to answer the research question whether the Nd demand for wind turbines and EVs required to follow the Roadmap to Net Zero report by the IEA can be met, and finally, the overall future demand of Nd for all applications is compared to supply.

4.1 Discussion of the model results

If the Nd demand for EVs and wind turbines are compared, the demand for EVs is larger than the one for wind turbines, especially for the high demand scenario (Figure 19 and Figure 20). Only during the first decade (2021 to 2030) under the low demand scenario, which combines the LDS scenario for wind turbines and the low Nd intensity Scenario with behavioural change for EVs, the demand for wind turbines and EVs is the same. However, the demand for EVs then increases much faster as ICE cars are phased out and all cars sold are EVs, while the demand increase for wind turbines is less steep and reaches a peak in the late 2030s (Figure 21). Under both, the low and high demand scenario, the cumulative demand for the 2030s is only insignificantly higher than the demand for the 2040s (Figure 19 and Figure 20). The reason for this observation is the peak for Nd demand in wind turbines shortly before 2040 and the roughly symmetric increase and decrease of the demand curve, as well as the high number of retiring cars needing to be replaced in the 2040s.

When the low and high demand scenarios for wind are compared to each other, the high demand estimate (LDS) is 30 % higher than the low demand estimate (HDS) in the 2020s, and the difference increases to 51 % in the 2032s and 65 % in the 2040s as sub-technology share developments diverge.

For EVs, the difference between the low and high demand scenario - both assuming behavioural change - is larger, with the high estimate being about 4 times the low estimate.

This means that the uncertainty for Nd demand is mainly driven by the uncertainty over the Nd intensity of EVs, whereas the model for Nd demand for wind turbines is constrained much tighter. The high uncertainty about the Nd intensity of EVs is due to the relatively new technology and rapidly developing market as well as technology, which could mean that future Nd intensity might actually be lower than today if REE-free EV motors, that already exist (IEA 2021b; Blagoeva et al. 2016), gain significant market shares. The actual future Nd-intensity of EVs is therefore expected to be closer to the lower estimate.

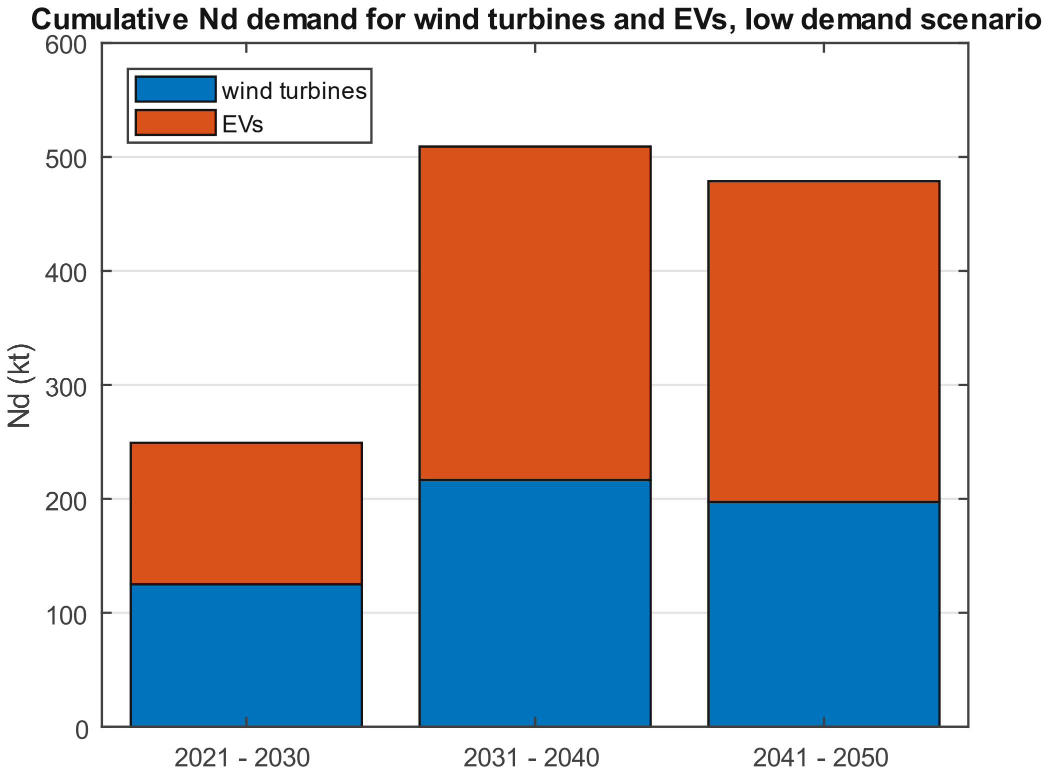


Figure 19 Cumulative Nd demand for wind turbines and EVs in each decade 2021 to 2050 under a low demand scenario (LDS for wind, low Nd intensity with behavioural change for EVs).

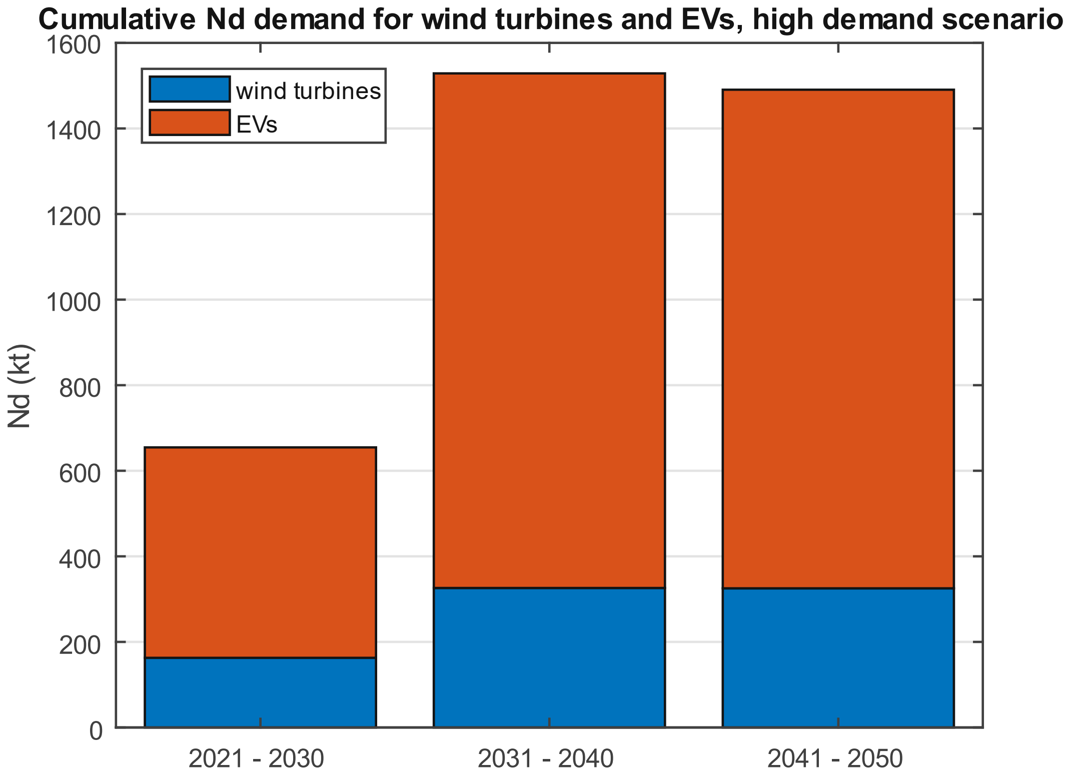


Figure 20 Cumulative Nd demand for wind turbines and EVs in each decade 2021 to 2050 under a high demand scenario (HDS for wind, high Nd intensity with behavioural change for EVs).

For the high and low demand scenarios visualized in Figure 19 and Figure 20, the LDS and HDS scenario for wind energy were chosen and only the scenario with behavioural change of car usage was considered for EVs. The rationale behind this decision is straight forward for wind turbines, as the LDS and HDS scenarios are the lowest and highest respectively. For EVs the scenario without behavioural change is used as an illustrative example to show the importance of behavioural change as it is done in the Net Zero 2050 Report. Behavioural change is an integral part of the pathway to a sustainable greenhouse gas neutral future. Without behavioural change, the Nd demand for EVs would be 1.3 times higher in the 2020s, 1.7 times higher in the 2030s and 2.5 times higher in the 2040s.

4.2 How can future demand for Nd in wind turbines and EVs be met?

To answer the question whether the modeled future demand for Nd in wind turbines and EVs can be met, the modeled demand is compared to the mining rate and the recycling potential. As for the discussion of the model results in Chapter 4.1, a low and a high demand scenario are constructed by combining the model results for wind turbines and EVs.

If the model results are compared to the current total mining production, it becomes clear that mining has to increase to satisfy the demand (Figure 21). However, the extent of the overshoot of demand is only minimal in the low demand scenario, where total Nd demand exceeds the current production by a few kt around the year 2035. Under the high demand scenario, on the other hand, demand already exceeds the current production in 2025, driven by the high demand for EVs. and stays above it from that year on.

The total recycling potential from EVs and wind turbines together is close to zero until the late 2030s and then increases rapidly with the same slope as the demand in the 2020s (Figure 21, dashed line). This means that recycling of Nd will not play a significant role in alleviating the pressure on mining in the short or medium term, a conclusion also drawn by earlier studies (Habib 2015). Under both scenarios, the total recycling potential is large enough to cover the Nd demand for wind turbines from about 2045 onwards and reaches about 60 % of the total demand. However, the recycling potential plus the current mining production summed up still cannot cover the total demand under the high demand scenario.

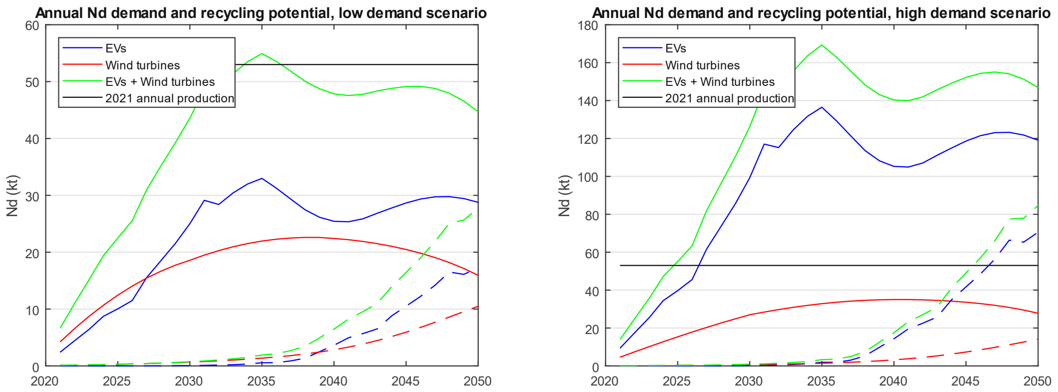


Figure 21 Annual Nd demand and recycling potential for EVs, wind turbines and both combined under a low demand scenario (LDS for wind, low Nd intensity with behavioural change for EVs) and under a high demand scenario (HDS for wind, high Nd intensity with behavioural change for EVs). The current (2021) annual mining production of Nd is shown as a black line. Note the different y-axes.

When the recycling potential is subtracted from demand, it is possible to obtain the mining need – the amount of Nd that has to be produced from mining to satisfy demand. The mining needs for the high and low demand scenarios are shown in Figure 22. Furthermore, the effect of behavioural change on the mining need is indicated through the dashed line which marks the mining need under scenarios without behavioural change.

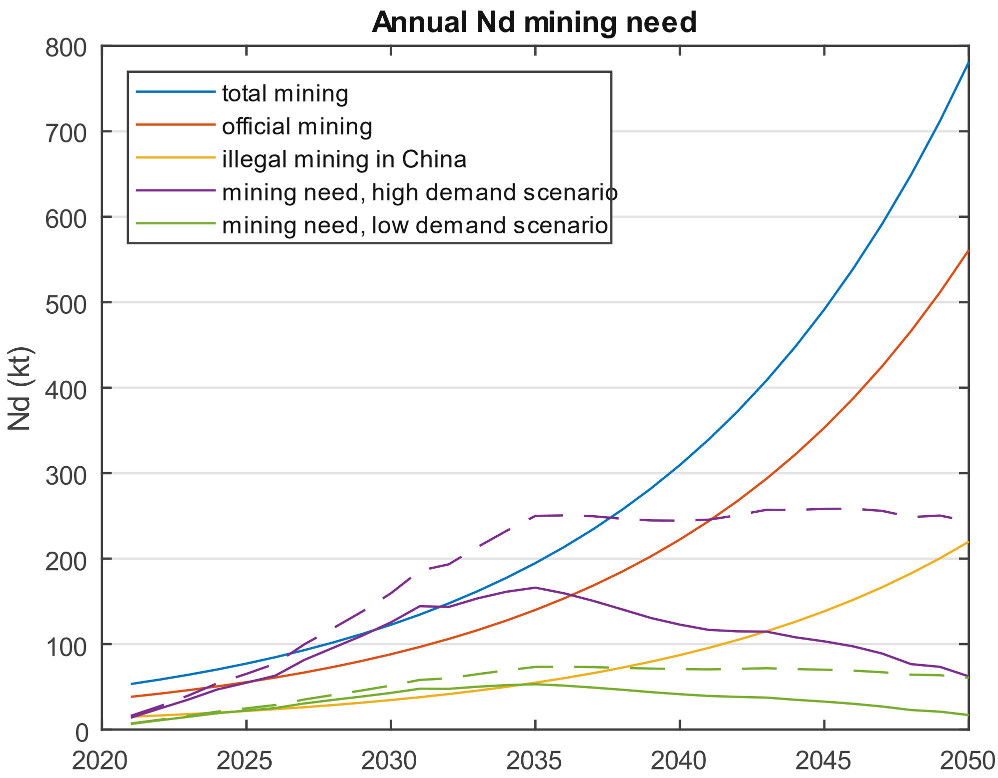


Figure 22 Annual amount of Nd required to be mined to cover the demand for Nd in wind turbines and EVs under a low and high demand scenario. The effect of behavioural change of car use is illustrated by adding a dashed line for a scenario without behavioural change.

In 2021, the modeled demand under the low demand scenario is ~12 % of total Nd mining compared to ~26 % under the high demand scenario.

The mining need with behavioural change under the high demand scenario would already exceed the official mining capacity in 2025 and the total mining capacity including illegal mining in China in 2030. If there is no behavioural change, the mining capacities would be exceeded already 2 to 3 years earlier. For the low demand scenario, the prospect is better and the mining need for wind energy and EVs would not exceed the official or total mining. Under all scenarios, mining need reaches a peak in 2035 and then decreases in the model with behavioural change or stabilizes without behavioural change. This means that from 2035 on, mining capacity does not need to increase to be able to satisfy the demand of Nd for wind turbines and EVs.

However, it is important to keep in mind that Nd is also required for other applications and Nd used in wind turbines and EVs only made up 26 % of the total demand in the EU in 2016 (Ciacci et al. 2019) and the share of permanent magnets used in EVs and wind turbines was only 14 % and 17 % respectively worldwide in 2015 (Constantinides 2016).

4.3 *Assessment of overall supply and demand for Nd*

To estimate the total demand development for Nd including other uses of the metal like home appliances, ICE vehicles, electronics and general machinery and others, two literature sources are used. Deetman et al. (2018) modeled the demand for Nd in home appliances, as well as for electricity generation and cars, for the shared socioeconomic pathway based on the global integrated assessment model IMAGE. Their data for appliances is used (~8 kt Nd in 2020, ~10 kt in 2030, and 15 kt in 2050 under the low demand scenario, which is deemed most realistic). However, since other uses are not integrated into the model, the relative share for Nd uses in China of 2016 from Geng et al. (2020) is taken to estimate the remaining Nd demand. According to Geng et al. (2020), about twice the amount of Nd used in home appliances is used in all other uses excluding wind energy and cars, which are already covered by the model of this study. It follows, that the total demand for Nd other than cars and wind energy can be approximated by multiplying the Nd demand for appliances by 3, assuming that Nd demand increases at the same rate across all the sectors. ICE sales numbers are taken from the model of this study and a Nd intensity of 200 g Nd is used to calculate the Nd demand.

Comparing the model result for 2021 to the supply of Nd for the same year (~53 kt total, 38 kt official mining) shows that the estimate is plausible as total Nd would reach ~42 – 51 kt.

The results for total Nd demand compared to mining production is shown in Figure 23. For Figure 24, it was assumed that 50 % of the annual demand for applications other than EVs and wind turbines can be met by recycling, which is slightly less than assumed for EVs.

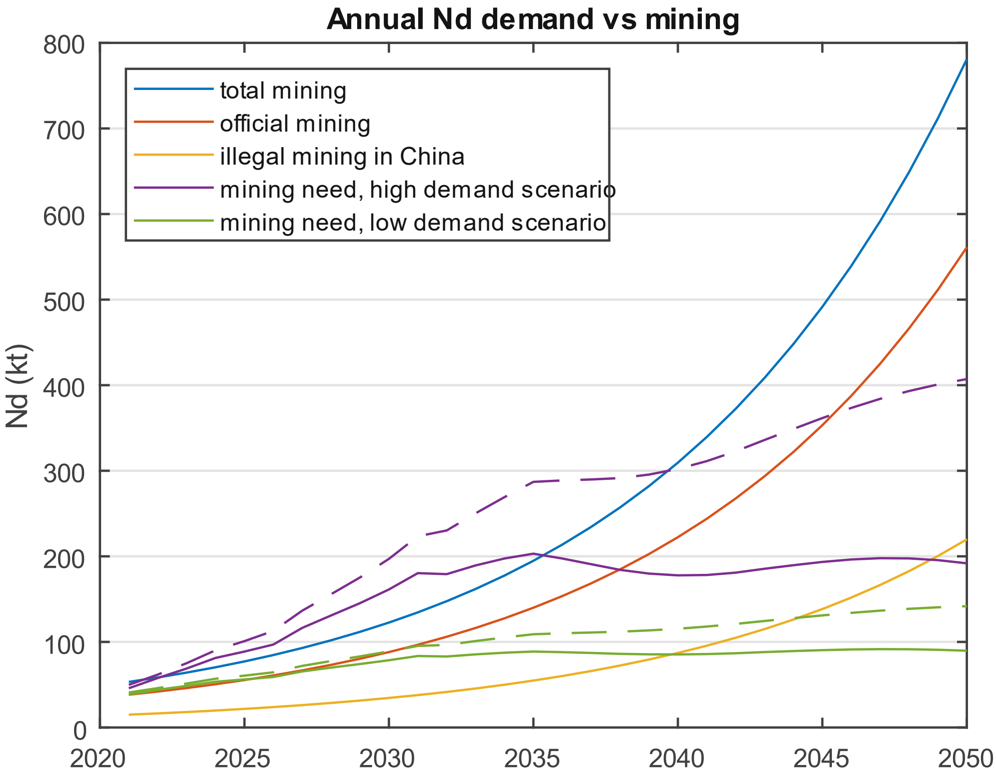


Figure 23 Total annual Nd demand compared to mining. Dashed lines indicate scenarios without behavioural change.

Figure 23 shows clearly, that total demand under a high demand scenario would exceed the mining capacity until 2035 or even 2040 if no behavioural change occurs. Nd demand under the low demand scenario is approximately equal to the official mining until 2030 when Nd demand levels off. This means that under the low demand scenario there is no risk for supply if China cracks down on illegal mining.

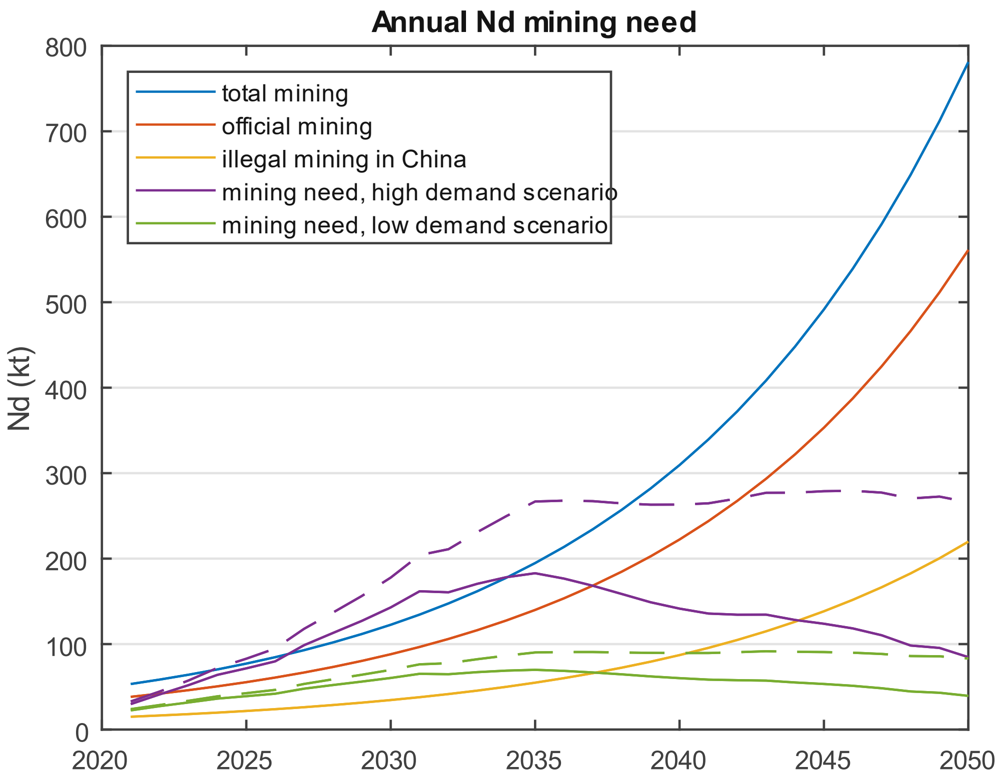


Figure 24 Total annual Nd mining need compared to mining. Dashed lines indicate scenarios without behavioural change.

The Nd mining need, which assumes that the recycling potential for Nd is realized from 2021 on, shows, that with recycling it would already be possible to meet demand without illegal mining in China. Comparing the total mining need to the mining need for wind energy and EVs, the difference is not very large since it is assumed that recycling covers half of the demand for uses other than wind and EV. However, since the current recycling rate for Nd is below 1 % (Yao et al. 2021), the scenario without recycling shown in Figure 23 is more realistic until at least 2030.

5. Conclusion

The following conclusions are drawn from this study:

1. The demand for Nd in EVs is larger than the Nd demand in wind turbines.
2. The Nd intensity and scenarios for wind turbines are much better constrained and more similar to each other than the modeled scenarios for EVs.
3. With the current mining rate, the Nd demand for EVs and wind turbines cannot be met, mining needs to increase.

4. Recycling of Nd from end-of-life EVs and wind turbines will not play an important role in the supply of Nd in the short or mid-term but increases after 2035.
5. By 2050, recycling of Nd from wind turbines and EVs can partly offset the demand for primary Nd: ~50 % – 68 % of the Nd demand for wind turbines and 32 % – 60 % for EVs could be covered by recycling in 2050.
6. If mining increases by ~10 % annually, the demand for primary Nd for the production of wind turbines and EVs could exceed mining around 2030 or even earlier and longer (from 2025 to 2037) if illegal mining in China stops.
7. The modeled total demand for Nd including uses other than wind turbines and EVs exceeds Nd mining until 2035 under the high demand scenario, whereas official mining would be enough to cover the total Nd demand under the low demand scenario.

For future research, the model for Nd demand in cars could be refined with respect to the development of car sales and Nd intensities once the technology is more widely adopted. Moreover, it would be interesting to integrate the demand for home appliances needed to ensure adequate living standards for the global population into the model. With respect to the goal of achieving a truly circular economy, the year from which on no more mining would be necessary and all demand for new products can be covered from recycled Nd recovered from EOL-products could be calculated. However, this can only happen once demand for Nd-containing products stabilizes or technological advance and substitution of Nd offset the increase in demand.

With respect to coupled production of metals, the consequences for the over- or undersupply of metals that are mined together with Nd could be examined and the economic implications.

Geopolitically, the criticality of raw materials such as Nd and concentration of the production and processing is an important security issue (Li et al. 2020). The potential to diversify supply based on the global distribution of Nd reserves and the implications of closing the loop and moving to a more circular economy would be interesting to assess.

Last but not least, the methods used to assess the demand and supply of Nd could be applied to other critical and non-critical raw materials that play a role in achieving sustainable development.

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Annex

Annex 1 MatLab code used for modelling and generation of figures

```
%%Fit curve for total installed wind capacity

%input data: from Net Zero 2050 report

x = [2019   2020  2025  2029  2030  2035  2040  2045  2050];
y = [628    742   1425  2712  3102  4977  6525  7645  8265];

%start x from 1
x = x-2018;
%fit 3rd degree polynome
fitcoeff = polyfit(x,y,3);

%calculate value for each year 2019 to 2050
plotx = (2019:2050);
ploty = zeros(1,length(plotx));
for i= 1:length(plotx)
%ploty (i) =
plotx(i).^3*fitcoeff(1)+plotx(i).^2*fitcoeff(2)+plotx(i)*fitcoeff(3
)+fitcoeff(4);
ploty (i) = i^3*fitcoeff(1) + i^2*fitcoeff(2) + i*fitcoeff(3)+
fitcoeff(4);
end


%plot
figure ('Name','polynomial fit 2019 to 2050')

plot(plotx,ploty,'DisplayName',"fitted curve")
hold on

%plot original points
plot((x+2018),y,'x','DisplayName',"data points")
hold off
legend('Location','northwest')
title("Polynomial fit 2019 to 2050")

%since the curve is too flat in the last 5 years, assume linear
growth here
ploty(32)= y(9);
for i=1:4
    ploty(27+i)=ploty(27)+(ploty(32)-ploty(27))/5*i;
end

%plot
figure ('Name','Linear fit 2045 to 2050')

plot(plotx,ploty,'DisplayName',"fitted curve")
hold on

%plot original points
plot((x+2018),y,'x','DisplayName',"data points")
hold off
```

```
legend('Location','northwest')
title ("linear fit 2045 to 2050")

%% Weibull lifetime-function Wind Turbines

%Weibull functions: shape parameter B=5.1
%scale parameter A= expected lifetime

x = linspace (0,50,51);     %linspace over 50 years

wbl25=zeros(1,53) ;          %extra zeros
wbl25(1:51)=wblpdf(x,25,5.1);     %25 years (onshore)

wbl30=zeros(1,53)   ;        %extra zeros
wbl30(1:51)=wblpdf(x,30,5.1);     %30 years (offshore)


%annual installed capacity in GW
TotalCap = [741   653   591   539   487   436   371   319   283   237
      195   158   121   94    74    59    48    39    31    24    18
      14    10    7];            %total capacity from 2020 to 1997
(sorted descending)
TotalOffshore = [32,4560000000000 25,6520000000000 21,5760000000000
      17,2510000000000 13,8820000000000 12,0870000000000
      8,11100000000000 7,00800000000000 5,20400000000000
      3,48200000000000 3,12200000000000 2,12300000000000
      1,52900000000000 1,15300000000000 0,938000000000000
      0,737000000000000,644000000000000,553000000000000
      0,256000000000000,096000000000000     0,086000000000000
      0,032000000000000     0,032000000000000
      0,029000000000000];  %total installed offshore capacity from
2020 to 1997 (sorted descending)
%load Nd demand for wind under different scenarios (2020 to 2050)
Nddemand = [5360 2921  4544  6031  7382  8600  9685  10638 11459
      12150 12711 13664 14500 15216 15810 16279 16623 16842 16940
      16919 16784 16540 16190 15738 15182 14518 13739 12831 11778
      10559 9150
5449  2994  4696  6284  7755  9107  10339 11447 12430 13285 14009
      15106 16079 16924 17637 18212 18650 18949 19111 19139 19037
      18809 18458 17987 17394 16674 15817 14807 13623 12241 10631
5449  3133  4985  6764  8462  10070 11580 12985 14274 15440 16473
      17955 19312 20532 21606 22523 23277 23862 24274 24515 24583
      24482 24212 23771 23156 22356 21354 20125 18639 16855 14730
4904  2648  4081  5365  6504  7504  8367  9098  9702  10181 10540
      11293 11947 12498 12946 13290 13530 13668 13707 13651 13503
      13270 12953 12556 12080 11521 10873 10128 9273  8292  7167
4904  2557  3799  4802  5584  6161  6549  6763  6821  6738  6529  6825
      7041  7180  7246  7245  7180  7058  6884  6663  6404  6264  6086
      5872  5624  5339  5016  4652  4240  3774  3248
537   1304  2016  2677  3286  3845  4352  4807  5212  5566  5869  5821
      5777  5739  5706  5681  5663  5655  5657  5671  5628  5658  5705
      5769  5853  5958  6084  6230  6398  6584  6786
574   1442  2310  3183  4059  4940  5824  6713  7607  8506  9411  9367
      9326  9290  9262  9242  9233  9236  9256  9293  9353  9437  9549
      9693  9870  10084 10335 10624 10950 11311 11703
585   1484  2401  3339  4297  5277  6278  7300  8344  9411  10501
      10451 10406 10366 10334 10312 10302 10306 10327 10370 10436
      10530 10655 10815 11013 11252 11532 11854 12218 12621 13058
```

```
734   1856  2996  4158  5341  6546  7774  9023  10296 11592 12913
      12882 12857 12839 12830 12833 12850 12886 12944 13027 13141
      13260 13418 13619 13868 14168 14521 14927 15386 15893 16443
734   1822  2890  3938  4968  5980  6974  7950  8909  9851  10776
      10652 10532 10420 10315 10221 10139 10070 10019 9987  9978  9946
      9940  9964  10018 10104 10221 10369 10545 10746 10966];
%%
%  onshore LDS
%
% onshore MDS
%
% onshore HDS
%
%  onshore IEA baseline
%
%  onshore IEA constrained REE
%
%  offshore LDS
%
%  offshore MDS
%
%  offshore HDS
%
%  offshore IEA baseline
%
%  offshore IEA constrained REE
%% calculate the capacity growth and sort from 1998 to 2050

% capacity growth
dcap = zeros(1,53);
%placeholder for difference in capacity (capacity growth)
doffshore = zeros(1,53);
for i=1:23                                              %invert
vectors
    dcap(i) = (TotalCap(24-i)-TotalCap(24-i+1));            %total
    doffshore(i) = (TotalOffshore(24-i)-TotalOffshore(24-i+1));
%offshore
end

donshore=dcap-doffshore;
%donshore only 1998 to 2021
%%
% load the growth in offshore capacity from 2021 to 2050 (30 years)

%offshore capacity growth doffshore
offshore20 = [12.5     20    27.5  35    42.5  50    57.5  65    72.5
      80    79.5  79    78.5  78    77.5  77    76.5  76    75.5  75
      74.5  74    73.5  73    72.5  72    71.5  71    70.5  70];
%linear growth assumed, taken from excel

doffshore(24:end)=offshore20;   %24th value is year 2021
%%
% load the total installed capacity from 2019 to 2050 (from
fitcurve, 32
% values), and calculate growth for 2021 until 2050
%
% and substract offshore to get onshore
```

```
%calculate onshore capacity growth donshore
ploty = [622      689    796    940    1117  1326  1562  1824  2108  2412
      2732  3066  3411  3764  4122  4482  4841  5197  5547  5887  6216
      6529  6825  7100  7351  7576  7771  7934  8062  8153  8202
      8208];            %polynomial fit 2019 until 2050
%load('fit_installed_19_45','ploty');           %for linear prowth
from 2045 to 2050
for i=1:30
%2021 until 2050 are 30 years to calculate
    donshore(23+i)=ploty(i+1)-ploty(i) - doffshore(23+i);
%4th value is year 2021
end
%%
% total capacity growth dcap

dcap(24:53) = ploty(3:32)-ploty(2:31);     %1998 until 2050
%% Offshore added capacity
% # matrix with weibull*installed capacity in the rows and lines
are years from
% 1998 to 2050 (since weibull starts with 0, we also will add the
zero from weibull
% 2050 in 2050)
%%

wbloff=zeros(53,55);        %weibull offshore dimension: 53x55
zeros (need some extra zeros at the end)
for i=1:53
    wbloff(i,1:53)=wbl30.*doffshore(i);    %from 1998 until 2050 ->
53
end
%%
%     2.  Add all weibull functions up, and put them into
addoffshore

addoffshore = 1:30;                  %we calculate the added
capacity for 2021-2050 -> 30
retiredall=zeros(1,30);
for i=1:30
    retired= 0;                            %we calculate retired
capacity for 2021-2050 -> 30
    for   j=1:(23+i)                         %2021 as start year has
24 years from 1998 to 2021
        retired = retired + wbloff(j,(24+i-j));        %add for
each year j from 1998 on the retired (wbloff)
    end
retiredall(i)=retired;
  addoffshore(i)= doffshore(23+i) + retiredall(i);
%doffshorefor 2021 is 24th value in doffshore

end
%%
%
%% Plot offshore
%%
%plot

plotx=2021:2050;
plot(plotx,addoffshore,'DisplayName',"added offshore")
```

```
axis([2020 2050 0 100])
%set axis limits
hold on
plot(plotx,retiredall,'DisplayName',"retired offshore")
plot(plotx,doffshore(24:53),'DisplayName',"offshore capacity
growth")
hold off
legend ('Location','northwest')

%% Onshore added capacity
% # matrix with weibull*installed capacity in the rows and lines
are years from
% 1998 to 2050 (since weibull starts with 0, we also will add the
zero from weibull
% 2050 in 2050)
%%

wblon=zeros(53,55);        %weibull offshore dimension: 53x55 zeros
(need some extra zeros at the end)
for i=1:53
    wblon(i,1:53)=wbl25.*donshore(i);    %from 1998 until 2050 ->
53
end
%%
%     2.  Add all weibull functions up, and put them into
addoffshore

addonshore = 1:30;                  %we calculate the added capacity
for 2021-2050 -> 30
retiredallon=zeros(1,30);
for i=1:30
    retired= 0;                            %we calculate retired
capacity for 2021-2050 -> 30
    for   j=1:(23+i)                         %2021 as start year has
24 years from 1998 to 2021
        retired = retired + wblon(j,(24+i-j));        %add for each
year j from 1998 on the retired (wbloff)
    end
retiredallon(i)=retired;
  addonshore(i)= donshore(23+i) + retiredallon(i);
%doffshorefor 2021 is 24th value in doffshore

end
% addoffshore(30) = doffshore
%%
%
%% Plot onshore
%%
%plot

plotx=2021:2050;
plot(plotx,addonshore,'DisplayName',"added onshore")
hold on
plot(plotx,retiredallon,'DisplayName',"retired onshore")
axis([2020 2050 0 400])
%set axis limits
plot(plotx,donshore(24:53),'DisplayName',"onshore capacity growth")
hold off
```

```
legend ('Location','northwest')
%% Total
% add onshore and offshore
%%
plotx=2021:2050;
plot(plotx,(addonshore+addoffshore),'DisplayName',"added total")
hold on
plot(plotx,(retiredall+retiredallon),'DisplayName',"retired total")
plot(plotx,donshore(24:53)+doffshore(24:53),'DisplayName',"capacity
growth total")
hold off
legend ('Location','northwest')
retiredtot = retiredall+retiredallon;
%% Without lifetime function, fixed age
% added capacity is growth in capacity + added capacity of 25 years
ago for
% onshore and 30 years ago for offshore

%total
%plot total installed capacity, retired capacity and capacity
growth

plotx = 1997:2050;

% %total installed capacity
% totalCaptot=zeros(1,54);
% for i=1:24
%     totalCaptot(i) = TotalCap(25-i);              %years 1997 to
2020 invert sorting
% end
% totalCaptot(25:54) = ploty (3:end);        %years 2021 to 2050
%
% plot(plotx,totalCaptot,'DisplayName',"total installed capacity")
% hold on


%%
% comment: up until here dcap was only filled until 2021 (wind
database
% values) the rest is filled in now from fitcurve

plot(plotx(2:end),dcap,'DisplayName',"capacity growth")
hold on
% retired capacity 25 years lifetime
retiredtot25 = zeros(1,29);                    %plotx has 54
values, starting at 25th we need 29
retiredtot25 = doffshore(1:29)+donshore(1:29);             %add
onshore and offshore growth
plot(plotx(26:end),(retiredtot25),'DisplayName',"retired (25 years
lifetime)")

% retired capacity 30 years lifetime
retiredtot30 = zeros(1,24);                    %plotx has 54
values, starting at 30th we need 24
retiredtot30 = doffshore(1:24)+donshore(1:24);             %add
onshore and offshore growth
plot(plotx(31:end),(retiredtot30),'DisplayName',"retired (30 years
lifetime)")
```

```
% % total added capacity
% plot(plotx(2:end),(doffshore+donshore),'DisplayName',"total added
capacity")
hold off
legend ('Location','northwest')
%% Recycling Potentential
%     technology shares 2010 (IEA, 2021)
%
%     onshore     offshore
%
% GB-DFIG           0,79         0,21
%
% GB-PMSG   0,02     0,25
%
% DD-PMSG   0,11     0,54
%
% DD-EESG           0,08         0,00
%%
%technology shares
techshare = [0.79 0.21, 0.02 0.25, 0.11 0.54, 0.08 0];
%%
% Nd intensities
%
%   * technology  t(Nd)/GW *
%
%    GB-DFIG  12
%
%    GB-PMSG  51
%
%    DD-PMSG  180
%
%    DD-EESG  28

%Nd intensities
intens = [12 51 180 28];
%% Annual Nd demand historic

%onshore 1998 to 2020
Ndon = donshore
(1:23).*(techshare(1)*intens(1)+techshare(3)*intens(2)+techshare(5)
*intens(3)+techshare(7)*intens(4));
%offshore 1998 to 2020
Ndoff = doffshore
(1:23).*(techshare(2)*intens(1)+techshare(4)*intens(2)+techshare(6)
*intens(3)+techshare(8)*intens(4));

%%
%weibull historic
wblhon=zeros(23,55);        %23 years, 51 and some zeros extra
for i=1:23
    wblhon(i,1:53)=wbl25.*Ndon(i);    %from 1998 to 2020 -> 23
end

wblhoff = zeros(23,55);
for i=1:23
    wblhoff(i,1:53)=wbl30.*Ndoff(i);    %from 1998 to 2020 -> 23
end
```

```
%%

%weibull onshore scenarios
wblonLDS=zeros(54,55);        %weibull offshore dimension: 31x55
zeros (need some extra zeros at the end)
wblon = zeros(31,55);         %reused each time
for i=1:31
    wblon(i,1:53)=wbl25.*Nddemand(1,i);    %from 2020 until 2050 ->
31
end
wblonLDS(1:23,1:55)=wblhon;
wblonLDS(24:54,1:55) = wblon;

wblonMDS=zeros(54,55);        %weibull offshore dimension: 31x55
zeros (need some extra zeros at the end)
wblon = zeros(31,55);
for i=1:31
    wblon(i,1:53)=wbl25.*Nddemand(2,i);    %from 1998 until 2050 ->
31
end
wblonMDS(1:23,1:55)=wblhon;
wblonMDS(24:54,1:55) = wblon;

wblonHDS=zeros(54,55);        %weibull offshore dimension: 31x55
zeros (need some extra zeros at the end)
wblon = zeros(31,55);
for i=1:31
    wblon(i,1:53)=wbl25.*Nddemand(3,i);    %from 1998 until 2050 ->
31
end
wblonHDS (1:23,1:55)= wblhon;
wblonHDS (24:54,1:55) = wblon;


wblonIEAb=zeros(31,55);        %weibull offshore dimension: 31x55
zeros (need some extra zeros at the end)

wblon = zeros(31,55);
for i=1:31
    wblon(i,1:53)=wbl25.*Nddemand(4,i);    %from 1998 until 2050 ->
31
end
wblonIEAb(1:23,1:55) = wblhon;
wblonIEAb (24:54,1:55) = wblon;


wblonIEAr=zeros(31,55);        %weibull offshore dimension: 31x55
zeros (need some extra zeros at the end)
wblon = zeros(31,55);
for i=1:31
    wblon(i,1:53)=wbl25.*Nddemand(5,i);    %from 1998 until 2050 ->
31
end
wblonIEAr (1:23,1:55) = wblhon;
wblonIEAr (24:54,1:55) = wblon;


%offshore scenarios
```

```
wbloff = zeros(31,55);          %reused each time
wbloffLDS=zeros(31,55);         %weibull offshore dimension: 31x55
zeros (need some extra zeros at the end)
for i=1:31
    wbloff(i,1:53)=wbl25.*Nddemand(6,i);    %from 1998 until 2050 -
> 31
end
wbloffLDS (1:23,1:55) = wblhoff;
wbloffLDS (24:54,1:55) = wbloff;
wbloff = zeros(31,55);          %reused each time

wbloffMDS=zeros(31,55);         %weibull offshore dimension: 31x55
zeros (need some extra zeros at the end)
for i=1:31
    wbloff(i,1:53)=wbl25.*Nddemand(7,i);    %from 1998 until 2050 -
> 31
end
wbloffMDS (1:23,1:55) = wblhoff;
wbloffMDS (24:54,1:55) = wbloff;
wbloff = zeros(31,55);          %reused each time

wbloffHDS=zeros(31,55);         %weibull offshore dimension: 31x55
zeros (need some extra zeros at the end)
for i=1:31
    wbloff(i,1:53)=wbl25.*Nddemand(8,i);    %from 1998 until 2050 -
> 31
end
wbloffHDS (1:23,1:55) = wblhoff;
wbloffHDS (24:54,1:55) = wbloff;
wbloff = zeros(31,55);          %reused each time

wbloffIEAb=zeros(31,55);         %weibull offshore dimension: 31x55
zeros (need some extra zeros at the end)
for i=1:31
    wbloff(i,1:53)=wbl25.*Nddemand(9,i);    %from 1998 until 2050 -
> 31
end
wbloffIEAb (1:23,1:55) = wblhoff;
wbloffIEAb (24:54,1:55) = wbloff;
wbloff = zeros(31,55);          %reused each time

wbloffIEAr=zeros(31,55);         %weibull offshore dimension: 31x55
zeros (need some extra zeros at the end)
for i=1:31
    wbloff(i,1:53)=wbl25.*Nddemand(10,i);    %from 1998 until 2050
-> 31
end
wbloffIEAr (1:23,1:55) = wblhoff;
wbloffIEAr (24:54,1:55) = wbloff;


%%
% Released


releasedallon=zeros(5,30);          %5 scenarios, for 2021-2050 ->
30
for i=1:30
```

```
    retired= 0;                                   %we calculate retired
capacity for 2021-2050 -> 30
    for   j=1:(23+i)                                %2021 as start year has
24 years from 1998 to 2021
        retired = retired + wblonLDS(j,(24+i-j));         %add for
each year j from 1998 on the retired (wbloff)
    end
releasedallon(1,i)=retired;
end

for i=1:30
    retired= 0;                                   %we calculate retired
capacity for 2021-2050 -> 30
    for   j=1:(23+i)                                %2021 as start year has
24 years from 1998 to 2021
        retired = retired + wblonMDS(j,(24+i-j));         %add for
each year j from 1998 on the retired (wbloff)
    end
releasedallon(2,i)=retired;
end

for i=1:30
    retired= 0;                                   %we calculate retired
capacity for 2021-2050 -> 30
    for   j=1:(23+i)                                %2021 as start year has
24 years from 1998 to 2021
        retired = retired + wblonHDS(j,(24+i-j));         %add for
each year j from 1998 on the retired (wbloff)
    end
releasedallon(3,i)=retired;
end

for i=1:30
    retired= 0;                                   %we calculate retired
capacity for 2021-2050 -> 30
    for   j=1:(23+i)                                %2021 as start year has
24 years from 1998 to 2021
        retired = retired + wblonIEAb(j,(24+i-j));         %add for
each year j from 1998 on the retired (wbloff)
    end
releasedallon(4,i)=retired;
end

for i=1:30
    retired= 0;                                   %we calculate retired
capacity for 2021-2050 -> 30
    for   j=1:(23+i)                                %2021 as start year has
24 years from 1998 to 2021
        retired = retired + wblonIEAr(j,(24+i-j));         %add for
each year j from 1998 on the retired (wbloff)
    end
releasedallon(5,i)=retired;
end

%offshore
releasedalloff=zeros(5,30);          %5 scenarios, for 2021-2050 ->
30
for i=1:30
```

```
    retired= 0;                                  %we calculate retired
capacity for 2021-2050 -> 30
    for   j=1:(23+i)                               %2021 as start year has
24 years from 1998 to 2021
        retired = retired + wbloffLDS(j,(24+i-j));        %add for
each year j from 1998 on the retired (wbloff)
    end
releasedalloff(1,i)=retired;
end
for i=1:30
    retired= 0;                                  %we calculate retired
capacity for 2021-2050 -> 30
    for   j=1:(23+i)                               %2021 as start year has
24 years from 1998 to 2021
        retired = retired + wbloffMDS(j,(24+i-j));        %add for
each year j from 1998 on the retired (wbloff)
    end
releasedalloff(2,i)=retired;
end

for i=1:30
    retired= 0;                                  %we calculate retired
capacity for 2021-2050 -> 30
    for   j=1:(23+i)                               %2021 as start year has
24 years from 1998 to 2021
        retired = retired + wbloffHDS(j,(24+i-j));        %add for
each year j from 1998 on the retired (wbloff)
    end
releasedalloff(3,i)=retired;
end

for i=1:30
    retired= 0;                                  %we calculate retired
capacity for 2021-2050 -> 30
    for   j=1:(23+i)                               %2021 as start year has
24 years from 1998 to 2021
        retired = retired + wbloffIEAb(j,(24+i-j));        %add for
each year j from 1998 on the retired (wbloff)
    end
releasedalloff(4,i)=retired;
end

for i=1:30
    retired= 0;                                  %we calculate retired
capacity for 2021-2050 -> 30
    for   j=1:(23+i)                               %2021 as start year has
24 years from 1998 to 2021
        retired = retired + wbloffIEAr(j,(24+i-j));        %add for
each year j from 1998 on the retired (wbloff)
    end
releasedalloff(5,i)=retired;
end
%%
% Plot
%%
%onshore

plotx = 2021:2050;
```

```
%LDS
plot(plotx,releasedallon(1,1:end),'DisplayName','LDS');
hold on
%MDS
plot(plotx,releasedallon(2,1:end),'DisplayName','MDS');
%HDS
plot(plotx,releasedallon(3,1:end),'DisplayName','HDS');
%IEAb
plot(plotx,releasedallon(4,1:end),'DisplayName','IEA baseline')
%IEAr
plot(plotx,releasedallon(5,1:end),'DisplayName','IEA constrained
REE')
hold off
legend ('Location','northwest')
title("Nd stocks released from onshore wind turbines")
ylabel("t Nd released")
%ofshore
%LDS
plot(plotx,releasedalloff(1,1:end),'DisplayName','LDS');
hold on
%MDS
plot(plotx,releasedalloff(2,1:end),'DisplayName','MDS');
%HDS
plot(plotx,releasedalloff(3,1:end),'DisplayName','HDS');
%IEAb
plot(plotx,releasedalloff(4,1:end),'DisplayName','IEA baseline')
%IEAr
plot(plotx,releasedalloff(5,1:end),'DisplayName','IEA constrained
REE')
hold off
ylabel("t Nd released")
title("Nd stocks released from offshore wind turbines")
legend ('Location','northwest')


%% Weibull lifetime-function for EVs

%Weibull functions: shape parameter B=5
%scale parameter A= expected lifetime = 17 years

x = linspace (0,50,51);     %linspace over 50 years
wbl17=zeros(1,51) ;          %zeros
wbl17(1:51)=wblpdf(x,17,5);     %17 years

% historic stock of PHEV and BEV cars (2010 to 2020 -> 11 values)
hPHEV = [10000   60000      120000     230000     410000
      730000     1180000 1930000 3260000     4760000 6850000];
hBEV = [10000    70000 170000     300000     520000     820000
      1210000    1830000    2370000    3350000];
hFCEV = [0 0 0 0 0 0 0 0 0 0 34800];

% % %required stock of cars in total with gradual behavioural
change 2021 to 2050
% % load('stockwc','stockwc');
% % %required stock of cars without behavioural change 2021 to 2050
% % load('stockwoc','stockwoc');
```

```
%historic car sales 2005 to 2020
hSales = [59825389.99  62116927.53 65359757.31 62114472.25
      60399932.78 69107376.96 72212768.99 74636518.9  77780734.07
      80743686.94 84606783.49 89119741.73 91207161.3  91232899.85
      86892329    73197606.2];

%sales from 2021 to 2050 with and without bahavioural change
salesw = zeros (1,30);                    %to be filled later
saleswo = zeros (1,30);                    %to be filled later

%empty: weibull for car sales from 2005 to 2049 with and without
change
wblSaleswc=zeros(45,51);
wblSaleswoc=zeros(45,51);

%empty: all retired each year from 2021 to 2050
retiredall = zeros (1,30);
%need 2 different redired alls: with and without change
retiredallw = retiredall;
retiredallwo = retiredall;
%% Annual growth of car stock
%%
%with behavioural change
dwc = zeros(1,30);
%without behavioural change
dwoc = zeros (1,30);
%%
% *fit function* without behavioural change

%%Fit curve for car stocks without behavioural change

%input data: from Net Zero 2050 report

x = [2021 2030   2040  2050];
y = [1.447038 1.491962 1.812013 2.318760];

%start x from 1
x = x-2020;
%fit 3rd degree polynome
fitcoeff = polyfit(x,y,2);

%calculate value for each year 2021 to 2050
plotx = (2021:2050);
ploty = zeros(1,length(plotx));
for i= 1:length(plotx)
%ploty (i) =
plotx(i).^3*fitcoeff(1)+plotx(i).^2*fitcoeff(2)+plotx(i)*fitcoeff(3
)+fitcoeff(4);
ploty (i) = (i)^2*fitcoeff(1) + (i)*fitcoeff(2)+ fitcoeff(3);

end


%plot
figure ('Name','Car stocks without behavioural change 2021 to
2050')

plot(plotx,ploty,'DisplayName',"fitted curve")
```

```
hold on

%plot original points
plot((x+2020),y,'x','DisplayName',"data points")
hold off
legend('Location','northwest')
title("Car stocks without behavioural change 2021 to 2050")

stockwoc = ploty.*10^9;

%stock change without behavioural change 2021 to 2050
dowc = zeros (1,30);
dowc(1) = 0;                %assuming no stock change in 2021
for i=2:30
    dwoc(i)= stockwoc(i)-stockwoc(i-1);
end
%%
%
%
%
%
% *fit function* stock of cars 2021 to 2050 with behavioural change
%%
%%Fit curve for car stocks with behavioural change

%input data: from Net Zero 2050 report

x = [2020 2030   2040  2050];
y = [1.348772 1.243302      1.208009 1.159380];

%start x from 1
x = x-2019;
%fit 3rd degree polynome
fitcoeff = polyfit(x,y,2);

%calculate value for each year 2020 to 2050
plotx = (2020:2050);
ploty = zeros(1,length(plotx));
for i= 1:length(plotx)
% ploty (i) =
plotx(i).^3*fitcoeff(1)+plotx(i).^2*fitcoeff(2)+plotx(i)*fitcoeff(3
)+fitcoeff(4);
ploty (i) = (i)^2*fitcoeff(1) + (i)*fitcoeff(2)+ fitcoeff(3);

end


%plot
figure ('Name','Car stocks with gradual behavioural change 2021 to
2050')

plot(plotx,ploty,'DisplayName',"fitted curve")
hold on

%plot original points
plot((x+2019),y,'x','DisplayName',"data points")
hold off
legend('Location','northeast')
```

```
title("Car stocks with gradual behavioural change 2021 to 2050")

stockwc = ploty.*10^9;

%stock change with behavioural change
dwc = zeros(1,1);
for i=1:30
    dwc(i)= stockwc(i+1)-stockwc(i);
end
%% Retiring each year 2021 to  2031
% with a fixed lifetime of 17 years, assuming 10% less car-sales
for 2004 than
% for for 2005
%%
retiredall (1) =hSales(1)*0.9;
for i=1:10                      %from hsales 2005 to 2014
    retiredall(i+1)=hSales(i);  %retired all filled for 2021 to
2031
end

%need 2 different redired alls: with and without change
retiredallw = retiredall;
retiredallwo = retiredall;

%%
%
üüüüüüüüüüüüüüüüüüüüüüüüüüüüüüüüüüüüüüüüüüüüüüüüüüüüüüüüüüüüüüüüüüüüü
üüüüüüüüüüüüüüüüüüüüüüüüüüüüü
%% Weibull Matrix with retiring cars (wblSales)
% always shift next row 1 to the right --> one column are all to
sum up to get
% the retiring
%
% 2005 to 2050
%
% since after 27 years all cars are retired, only 27 needed to sum
up: i
% to (26+i)
%%
%fill in historic from 2005 to 2020 (same for both scenarios w/wo
change)
for i=1:16
    wblSaleswc(i,i:26+i)=hSales(i).*wbl17(1:27);
    wblSaleswoc(i,i:26+i)=wbl17(1:27).*hSales(i);
end
%%
% since we assume a fixed lifetime for all curs until 2031, the car
sales
% for 2021 to 2031 are retiring + stock change

for i=1:11
    salesw (i) = retiredallw(i) + dwc(i);
    saleswo (i) = retiredallwo(i) + dwoc(i);
end
%% Sales each year from 3032 to 2050 without behavioural change
%
%%
for i=1:19                      %2032 to 2050 are 19
```

```
    %retiring
    retired= 0;                                %start from 0 again
    for   j=1:(27)                           %27 added up each
        retired = retired + wblSaleswoc(27+i-j,27+i);        %for
2005 2032 is the 27th value, then counting down 27 rows
    end


saleswo (i+11) = retired + dwoc(i+11);                    %sales
from 2032ff, 11 are already filled

wbli = wbl17.*saleswo(i);                       %wbl only 27 values
needed
wblSaleswoc (16+i,16+i:42+i) = wbli(1:27);           %2021 is 17th
year from 2005

retiredallwo(i+11)=retired;                              %fill in
retired of 2032ff, 11 are already filed
end
%%
% Plot from 2021 to 2050 growth of stock, sales and retiring
%%
plotx = 2021:2050;

 %growth of stocks
p0= plot(plotx,dwoc,'DisplayName','car stock change');
hold on

%sales all from 2005 on
sales(1:16)=hSales;
sales(17:46) = saleswo;

p1= plot(2005:2050,sales,'DisplayName','car sales');


%retiring
p2= plot(plotx,retiredallwo,'DisplayName','retired cars');

%zero line
p3= plot(2005:2050,zeros(1,46),'k');

legend ([p0 p1 p2],'Location','northwest')
hold off

set(gca,'XGrid','on','YGrid','off')


%% Sales each year from 3032 to 2050 with behavioural change
%
üüüüüüüüüüüüüüüüüüüüüüüüüüüüüüüüüüüüüüüüüüüüüüüüüüüüüüüüüüüüüüüüüü
üüüüüüüüüüüüüüüüüüüüüüüüüüüü
%%
for i=1:19                      %2032 to 2050 are 19
    %retiring
    retired= 0;                                %start from 0 again
    for   j=1:(27)                           %27 added up each
        retired = retired + wblSaleswc(27+i-j,27+i);        %for
2005 2032 is the 27th value, then counting down 27 rows
```

```
    end

salesw (i+11) = retired + dwc(i+11);                    %sales from
2032ff, 11 are already filled

wbli = wbl17.*salesw(i);                          %wbl only 27 values
needed
wblSaleswc (16+i,16+i:42+i) = wbli(1:27);            %2021 is 17th
year from 2005

retiredallw(i+11)=retired;                              %fill in
retired of 2032ff, 11 are already filed
end
%%
% Plot from 2021 to 2050 growth of stock, sales and retiring
%%
plotx = 2021:2050;

 %growth of stocks
p0= plot(plotx,dwc,'DisplayName','car stock change');
hold on

%sales all from 2005 on
sales(1:16)=hSales;
sales(17:46) = salesw;

p1 = plot(2005:2050,sales,'DisplayName','car sales');


%retiring
p2= plot(plotx,retiredallw,'DisplayName','retired cars');

%zero line
p3= plot(2005:2050,zeros(1,46),'k');

legend ([p0 p1 p2],'Location','northwest')

set(gca,'XGrid','on','YGrid','off')
hold off
%% Nd demand for EVs 2021 to 2050
%% Sold EVs 2021 to 2050
% based on the technology share of car sales
%%
%import technology shares 2021 to 2035 (BEV, PHEV, FCEV)
Techshare = [0.0798    0.1316      0.1834      0.2352      0.287
      0.3388      0.3906      0.4424      0.4942      0.546 0.6172
      0.6884      0.7596      0.8308      0.902
0.0178      0.0236      0.0294      0.0352      0.041 0.0468
      0.0526      0.0584      0.0642      0.07  0.05684     0.04368
      0.03052     0.01736     0.00419999999999999
0.00308     0.00596     0.00884     0.01172     0.0146      0.01748
      0.02036     0.02324     0.02612     0.029 0.0418      0.0546
      0.0674      0.0802      0.093];
techshare(1,16:30)=techshare(1,15);     %2036 to 2050 is same as
2035
techshare(2,16:30)=techshare(2,15);     %2036 to 2050 is same as
2035
```

```
techshare(3,16:30)=techshare(3,15);     %2036 to 2050 is same as
2035
%%
% Without behavioural change

BEVwo = zeros(1,30);                    %nuber of sold BEV 2021 to 2050
PHEVwo = zeros (1,30);                  %nuber of sold PHEV 2021 to
2050
FCEVwo = zeros (1,30);                  %nuber of sold FCEV 2021 to
2050
for i=1:30
    BEVwo (i) = techshare(1,i)*saleswo(i);
    PHEVwo(i) = techshare(2,i)*saleswo(i);
    FCEVwo (i) = techshare(3,i)*saleswo(i);
end
%%
% With behavioural change

BEVw = zeros(1,30);                    %nuber of sold BEV 2021 to 2050
PHEVw = zeros (1,30);                  %nuber of sold PHEV 2021 to 2050
FCEVw = zeros (1,30);                  %nuber of sold FCEV 2021 to 2050
for i=1:30
    BEVw (i) = techshare(1,i)*salesw(i);
    PHEVw(i) = techshare(2,i)*salesw(i);
    FCEVw (i) = techshare(3,i)*salesw(i);
end

xlswrite('EV',BEVw,'A1:AD1')
xlswrite('EV',PHEVw,'A2:AD2')
xlswrite('EV',FCEVw,'A3:AD3')
xlswrite('EV',BEVwo,'A4:AD4')
xlswrite('EV',PHEVwo,'A5:AD5')
xlswrite('EV',FCEVwo,'A6:AD6')
%% ICE sales
%%
ICEwo = saleswo-(BEVwo + PHEVwo + FCEVwo);
ICEw = salesw - (BEVw + PHEVw + FCEVw);


%% Wind turbine recycling Potential


%Weibull functions: shape parameter B=5.1
%scale parameter A= expected lifetime

x = linspace (0,50,51);     %linspace over 50 years

wbl25=zeros(1,53) ;          %extra zeros
wbl25(1:51)=wblpdf(x,25,5.1);     %25 years (onshore)

wbl30=zeros(1,53)   ;        %extra zeros
wbl30(1:51)=wblpdf(x,30,5.1);     %30 years (offshore)

%annual installed capacity in GW
TotalCap = [741   653   591   539   487   436   371   319   283   237
      195   158   121   94    74    59    48    39    31    24    18
      14    10    7];            %total capacity from 2020 to 1997
(sorted descending)
```

```
TotalOffshore = [32,4560000000000 25,6520000000000 21,5760000000000
      17,2510000000000 13,8820000000000 12,0870000000000
      8,11100000000000 7,00800000000000 5,20400000000000
      3,48200000000000 3,12200000000000 2,12300000000000
      1,52900000000000 1,15300000000000 0,938000000000000
      0,737000000000000,644000000000000,553000000000000
      0,256000000000000,096000000000000     0,0860000000000000
      0,0320000000000000     0,0320000000000000
      0,0290000000000000];  %total installed offshore capacity from
2020 to 1997 (sorted descending)

%%
% calculate the capacity growth and sort from 1998 to 2050

% capacity growth
dcap = zeros(1,53);
%placeholder for difference in capacity (capacity growth)
doffshore = zeros(1,53);
for i=1:23                                                  %invert
vectors
    dcap(i) = (TotalCap(24-i)-TotalCap(24-i+1));            %total
    doffshore(i) = (TotalOffshore(24-i)-TotalOffshore(24-i+1));
%offshore
end

donshore=dcap-doffshore;
%donshore only 1998 to 2021
%%
% load the growth in offshore capacity from 2021 to 2050 (30 years)
%
% [check if this ist still true or whole 1997 to 2050]

%offshore capacity growth doffshore
offshore20 = [12.5     20    27.5  35    42.5  50    57.5  65    72.5
      80    79.5  79    78.5  78    77.5  77    76.5  76    75.5  75
      74.5  74    73.5  73    72.5  72    71.5  71    70.5  70];
%linear growth assumed, taken from excel
doffshore(24:end)=offshore20;   %24th value is year 2021
%%
% load the total installed capacity from 2019 to 2050 (from
fitcurve, 32
% values), and calculate growth for 2021 until 2050
%
% and substract offshore to get onshore

%calculate onshore capacity growth donshore
ploty = [622      689   796   940   1117  1326  1562  1824  2108  2412
      2732  3066  3411  3764  4122  4482  4841  5197  5547  5887  6216
      6529  6825  7100  7351  7576  7771  7934  8062  8153  8202
      8208];            %load('fit_installed_19_45','ploty');
%for linear prowth from 2045 to 2050
for i=1:30
%2021 until 2050 are 30 years to calculate
    donshore(23+i)=ploty(i+1)-ploty(i) - doffshore(23+i);
%4th value is year 2021
end
%%
% total capacity growth dcap
```

```
dcap(24:53) = ploty(3:32)-ploty(2:31);     %1998 until 2050
%%
%     technology shares 2010 (IEA, 2021)
%
%     onshore     offshore
%
% GB-DFIG           0,79        0,21
%
% GB-PMSG   0,02     0,25
%
% DD-PMSG   0,11     0,54
%
% DD-EESG           0,08        0,00
%%
%technology shares
techshare = [0.79 0.21, 0.02 0.25, 0.11 0.54, 0.08 0];
%%
% Nd intensities
%
%   * technology  t(Nd)/GW *
%
%    GB-DFIG  12
%
%    GB-PMSG  51
%
%    DD-PMSG  180
%
%    DD-EESG  28

%Nd intensities
intens = [12 51 180 28];
%% Annual Nd demand

%onshore 1998 to 2020
Ndon = donshore
(1:23).*(techshare(1)*intens(1)+techshare(3)*intens(2)+techshare(5)
*intens(3)+techshare(7)*intens(4));
%offshore 1998 to 2020
Ndoff = doffshore
(1:23).*(techshare(2)*intens(1)+techshare(4)*intens(2)+techshare(6)
*intens(3)+techshare(8)*intens(4));

%%


%weibull
wblon=zeros(53,55);        %weibull offshore dimension: 53x55 zeros
(need some extra zeros at the end)
for i=1:53
    wblon(i,1:53)=wbl25.*donshore(i);    %from 1998 until 2050 ->
53
end
%%
%      2.  Add all weibull functions up, and put them into
addoffshore
```

```
addonshore = 1:23;                   %we calculate the added capacity
for 1998-2020 -> 23
retiredallon=zeros(1,30);
for i=1:23
    retired= 0;                             %we calculate retired
capacity for 1998-2020 -> 23
    for   j=1:(23+i)                          %2021 as start year has
24 years from 1998 to 2021
        retired = retired + wblon(j,(24+i-j));        %add for each
year j from 1998 on the retired (wbloff)
    end
retiredallon(i)=retired;
  addonshore(i)= donshore(23+i) + retiredallon(i);
%donshorefor 2021 is 24th value in donshore

end


%% Weibull functions

x = linspace (0,50,51);     %linspace over 50 years
% wblsekine = wblpdf(x,13.2,3.6)      %used by Sekine et al. 2017
for cars
wbl17(1:51) = wblpdf(x,17,5);     %17 years (cars)
wbl25(1:51)=wblpdf(x,25,5.1);     %25 years (onshore)
wbl30(1:51)=wblpdf(x,30,5.1);     %30 years (offshore)
wbl252(1:51)=wblpdf(x,17,2);       %shape parameter = 2
wbl2510(1:51)=wblpdf(x,17,10);       %shape parameter = 10
%plot
%plot(x,wblsekine,'DisplayName','Sekine et al. 2017')
plot(x,wbl17,'DisplayName','\alpha=5 \beta=17
(cars)','Color','blue')
hold on
plot(x,wbl25,'DisplayName','\alpha=5.1 \beta=25 (onshore wind)')
plot(x,wbl30,'DisplayName','\alpha=5.1 \beta=30 (offshore wind)')
plot(x,wbl252,'--','DisplayName','\alpha=2
\beta=17','Color','blue')
plot(x,wbl2510,'-.','DisplayName','\alpha=10
\beta=17','Color','blue')
hold off
legend ('show')
xlabel('x')
ylabel('frequency distribution')
%%
plotx = categorical({'2021 - 2030', '2031 - 2040','2041 - 2050'});

recpotLDStot = [124    157   195   240   292   351   417   492   576
      671   776   896   1031  1185  1363  1570  1813  2100  2439  2838
      3305  3846  4465  5162  5934  6773  7667  8600  9553  10507];
recpotHDStot = [124    157   195   240   292   351   418   493   578
      674   783   907   1050  1217  1415  1650  1934  2276  2690  3189
      3786  4491  5313  6257  7324  8506  9793  11167 12605 14081];
recpotEVlow = [0  0      0     0     0     0     3     17    35    62
      90    157   217   327   556   576   885   1365  2509  3636  4944
      5691  6518  8804  10511 12223 14183 16513 16100 17252];
recpotEVhigh = [00      0     0     0     0     8     54    126   219
      315   546   755   1118  1892  1931  3038  5314  9856  14338
      19541 22526 25828 34912 41708 48522 56323 66355 65317 70541];
```

```
recpotEVlown = [00      0      0      0      0      3      17     35     62
      90     157    217    327    556    576    885    1683   2898   4312   5985
      7175   8522   11405 13788 16252 19042 22379 23066 25578];
recpotEVhighn = [0      0      0      0      0      0      8      54     126
      219    315    546    755    1118   1892   1931   3038   6549   11380
      17003 23657 28400 33769 45229 54709 64516 75619 89926 93576
      104588];
%% Wind
%%
%demand total
winddemand = [120715    196807        115999; 141999    251173
      166834; 158450    304925        222360; 142141    238658
      161205; 116024    152434        75766];
vals = winddemand';
bar (plotx,vals.*10^(-3))
legend('LDS','MDS','HDS','IEA baseline','IEA constrained REE')
title('Cumulative Nd demand for wind turbines')
set(gca,'XGrid','off','YGrid','on')
ylabel('Nd demand (kt)')
%%

%plot annual 2021 to 2050
%load Nd demand for wind under different scenarios (2020 to 2050)
Nddemand = [5360 2921  4544  6031  7382  8600  9685  10638 11459
      12150 12711 13664 14500 15216 15810 16279 16623 16842 16940
      16919 16784 16540 16190 15738 15182 14518 13739 12831 11778
      10559 9150
5449  2994  4696  6284  7755  9107  10339 11447 12430 13285 14009
      15106 16079 16924 17637 18212 18650 18949 19111 19139 19037
      18809 18458 17987 17394 16674 15817 14807 13623 12241 10631
5449  3133  4985  6764  8462  10070 11580 12985 14274 15440 16473
      17955 19312 20532 21606 22523 23277 23862 24274 24515 24583
      24482 24212 23771 23156 22356 21354 20125 18639 16855 14730
4904  2648  4081  5365  6504  7504  8367  9098  9702  10181 10540
      11293 11947 12498 12946 13290 13530 13668 13707 13651 13503
      13270 12953 12556 12080 11521 10873 10128 9273  8292  7167
4904  2557  3799  4802  5584  6161  6549  6763  6821  6738  6529  6825
      7041  7180  7246  7245  7180  7058  6884  6663  6404  6264  6086
      5872  5624  5339  5016  4652  4240  3774  3248
537   1304  2016  2677  3286  3845  4352  4807  5212  5566  5869  5821
      5777  5739  5706  5681  5663  5655  5657  5671  5628  5658  5705
      5769  5853  5958  6084  6230  6398  6584  6786
574   1442  2310  3183  4059  4940  5824  6713  7607  8506  9411  9367
      9326  9290  9262  9242  9233  9236  9256  9293  9353  9437  9549
      9693  9870  10084 10335 10624 10950 11311 11703
585   1484  2401  3339  4297  5277  6278  7300  8344  9411  10501
      10451 10406 10366 10334 10312 10302 10306 10327 10370 10436
      10530 10655 10815 11013 11252 11532 11854 12218 12621 13058
734   1856  2996  4158  5341  6546  7774  9023  10296 11592 12913
      12882 12857 12839 12830 12833 12850 12886 12944 13027 13141
      13260 13418 13619 13868 14168 14521 14927 15386 15893 16443
734   1822  2890  3938  4968  5980  6974  7950  8909  9851  10776
      10652 10532 10420 10315 10221 10139 10070 10019 9987  9978  9946
      9940  9964  10018 10104 10221 10369 10545 10746 10966];
winddemandtot = 0;
winddemandtot (1,1:30)= Nddemand(1,2:end)+Nddemand(6,2:end);
winddemandtot (2,1:30)= Nddemand(2,2:end)+Nddemand(7,2:end);
winddemandtot (3,1:30)= Nddemand(3,2:end)+Nddemand(8,2:end);
```

```
winddemandtot (4,1:30)= Nddemand(4,2:end)+Nddemand(9,2:end);
winddemandtot (5,1:30)= Nddemand(1,2:end)+Nddemand(10,2:end);

%total wind
x = 2021:2050;
y = winddemandtot;
plot(x,y*10^(-3))
legend('LDS','MDS','HDS','IEA baseline','IEA constrained REE')
legend ('Location','northwest')
title('Annual Nd demand for wind turbines')
set(gca,'XGrid','off','YGrid','on')
ylabel('Nd (kt)')
%onshore
y = Nddemand(1:5,2:end);
plot(x,y*10^(-3))
legend('LDS','MDS','HDS','IEA baseline','IEA constrained REE')
legend ('Location','northwest')
title('Annual Nd demand for onshore wind turbines')
set(gca,'XGrid','off','YGrid','on')
ylabel('Nd (kt)')

%offshore
y = Nddemand (6:10,2:end);
plot(x,y*10^(-3))
legend('LDS','MDS','HDS','IEA baseline','IEA constrained REE')
legend ('Location','northwest')
title('Annual Nd demand for offshore wind turbines')
set(gca,'XGrid','off','YGrid','on')
ylabel('Nd (kt)')
%%

%recycling potential total
windrecpot = [3516     16010 65813; 3519 16629 75462; 3522 17111
      83323; 3517 16575 74854; 3515 15897 62505];
vals = windrecpot';
bar (plotx,vals.*10^(-3))
legend('LDS','MDS','HDS','IEA baseline','IEA constrained REE')
legend ('Location','northwest')
title('Cumulative Nd recycling potential from wind turbines')
set(gca,'XGrid','off','YGrid','on')
set(gca,'XGrid','off','YGrid','on')
ylabel('Nd (kt)')
%% EV
%%
EVdemand = [124135 292512 281536; 160603 497279     700046; 491829
1202630     1165314; 636389  2046790     2897584];
vals = EVdemand';
bar (plotx,vals.*10^(-3))
legend('low Nd-intensity, behavioural change','low Nd-intensity, no
behavioural change','high Nd-intensity, behavioural change','high
Nd-intensity, no behavioural change')
legend ('Location','northwest')
title('Cumulative Nd demand for EVs')
set(gca,'XGrid','off','YGrid','on')
ylabel('Nd demand (kt)')

%%
%plot annual 2021 to 2050
```

```
NdEV = [2408      4426  6413  8720  10037 11496 15527 18539 21557
        25014 29123 28395 30426 31985 32975 31259 29332 27445 26140
        25431 25350 25863 26850 27773 28655 29345 29735 29769 29432
        28764
2968  5110  7605  10556 12654 15030 20115 24318 28663 33584 39468
        40680 45111 49293 53254 53299 53254 53349 54095 55475 57498
        60119 63214 66249 69267 72125 74728 77030 79032 80784
9372  17382 25287 34464 39728 45552 61573 73559 85576 99335 117029
        115198      124410      131651      136490      129386
        121409      113598      108196      105264      104926
        107052      111135      114957      118605      121463
        123078      123218      121821      119058
11551 20070 29988 41723 50088 59557 79769 96489 113785      133368
        158600      165037      184458      202889      220427
        220610      220426      220819      223904      229620
        237992      248842      261652      274212      286703
        298536      309308      318839      327123      334375];
%total EV Nd demand, low int with beh cha; low int without beh cha;
high int beh ch; high int no beh ch
y = NdEV;
plot(x,y*10^(-3))
legend('low Nd-intensity, behavioural change','low Nd-intensity, no
behavioural change','high Nd-intensity, behavioural change','high
Nd-intensity, no behavioural change')
legend ('Location','northwest')
title('Annual Nd demand for EVs')
set(gca,'XGrid','off','YGrid','on')
ylabel('Nd (kt)')

%%
EVrecpot = [116  10318 112738; 116 11699 153192; 407 39102 451573;
407   44527 613990];
vals = EVrecpot';
bar (plotx,vals.*10^(-3))
legend('low Nd-intensity, behavioural change','low Nd-intensity, no
behavioural change','high Nd-intensity, behavioural change','high
Nd-intensity, no behavioural change')
legend ('Location','northwest')
title('Cumulative Nd recycling potential from EVs')
set(gca,'XGrid','off','YGrid','on')
ylabel('Nd (kt)')
%% Production
%%
Ndproduction = [53291  58460 64130 70351 77175 84661 92873 101882
        111764      122606      134498      147545      161856
        177557      194780      213673      234399      257136
        282078      309440      339456      372383      408504
        448129      491597      539282      591593      648977
        711928      780985
38291 42005 46079 50549 55452 60831 66732 73205 80305 88095 96640
        106014      116298      127579      139954      153529
        168422      184759      202680      222340      243907
        267566      293520      321992      353225      387488
        425074      466306      511538      561157
15000 16455 18051 19802 21723 23830 26142 28677 31459 34510 37858
        41530 45559 49978 54826 60144 65978 72378 79398 87100 95548
        104817      114984      126137      138373      151795
        166519      182671      200390      219828];
```

```
%
cumprodtot = [837193 2112963 5332835]; %cumulative Nd production
starting 2021
cumprod = [601544 1518216    3831773;235649   594747      1501063 ];
%official ; illegal
vals = cumprod';
bar (plotx,vals.*10^(-3),'stacked')
legend('official mining','illegal mining in China')
legend ('Location','northwest')
title('Cumulative Nd production')
set(gca,'XGrid','off','YGrid','on')
ylabel('Nd (kt)')
%%

%plot
y = Ndproduction;
plot(x,y.*10^(-3))
legend('total mining','official mining','illegal mining in China')
legend ('Location','northwest')
title('Annual Nd production')
set(gca,'XGrid','off','YGrid','on')
ylabel('Nd (kt)')
%% Total demand
% with behavioural change
%%
%low scenario: LDS for wind,  low Nd-intensity for EV
totdeml = [125055216572     197250; 124135   292512     281536];
%wind ; EV;

vals = totdeml';
bar (plotx,vals.*10^(-3),'stacked')
legend('wind turbines','EVs')
legend ('Location','northwest')
title('Cumulative Nd demand for wind turbines and EVs, low demand
scenario')
set(gca,'XGrid','off','YGrid','on')
ylabel('Nd (kt)')

%high scenario
totdemh = [162797326049     325228; 491829   1202630    1165314];
%wind ; EV
vals = totdemh';
bar (plotx,vals.*10^(-3),'stacked')
legend('wind turbines','EVs')
legend ('Location','northwest')
title('Cumulative Nd demand for wind turbines and EVs, high demand
scenario')
set(gca,'XGrid','off','YGrid','on')
ylabel('Nd (kt)')
%%
% plot
%%

%low: LDS, low with beh ch; sum of both
plot(x,NdEV(1,1:end).*10^(-3),'Color','b')
hold on
plot(x,winddemandtot(1,1:end).*10^(-3),'Color','r')
```

```
plot(x,(NdEV(1,1:end).*10^(-3)+winddemandtot(1,1:end).*10^(-
3)),'Color','g')
%2021 annual production
xx =[2021 2050];
yy = [53 53];
plot(xx,yy,'Color','k')
%recycling potential
plot(x,recpotEVlow.*10^(-3),'Color','b','LineStyle','--')
plot(x,recpotLDStot.*10^(-3),'Color','r','LineStyle','--')
plot(x,(recpotEVlow + recpotLDStot).*10^(-
3),'Color','g','LineStyle','--')
legend ('Location','northwest')
legend ('EVs','Wind turbines','EVs + Wind turbines','2021 annual
production')
title('Annual Nd demand and recycling potential, low demand
scenario')
set(gca,'XGrid','off','YGrid','on')
ylabel('Nd (kt)')

hold off

%high: HDS, high int with beh cha, sum of both
plot(x,NdEV(3,1:end).*10^(-3),'Color','b')
hold on
plot(x,winddemandtot(3,1:end).*10^(-3),'Color','r')
plot(x,(NdEV(3,1:end).*10^(-3)+winddemandtot(3,1:end).*10^(-
3)),'Color','g')
%2021 annual production
xx =[2021 2050];
yy = [53 53];
plot(xx,yy,'Color','k')
%recycling potential
plot(x,recpotEVhigh.*10^(-3),'Color','b','LineStyle','--')
plot(x,recpotHDStot.*10^(-3),'Color','r','LineStyle','--')
plot(x,(recpotEVhigh + recpotHDStot).*10^(-
3),'Color','g','LineStyle','--')
legend ('Location','northwest')
legend ('EVs','Wind turbines','EVs + Wind turbines','2021 annual
production')
title('Annual Nd demand and recycling potential, high demand
scenario')
set(gca,'XGrid','off','YGrid','on')
ylabel('Nd (kt)')
hold off
%%
%production, rec pot , prod-recpot

%with behavioural change
%production
y = Ndproduction;
plot(x,y.*10^(-3))
hold on
%rec pot high
%plot(x,(recpotEVlow + recpotLDStot).*10^(-3),'LineStyle','--')
%demand high - recpot
p1 = plot(x,(NdEV(3,1:end).*10^(-3)+winddemandtot(3,1:end).*10^(-
3)-(recpotEVhigh + recpotHDStot).*10^(-3)))
```

```
p2 = plot(x,(NdEV(1,1:end).*10^(-3)+winddemandtot(1,1:end).*10^(-
3)-(recpotEVlow + recpotLDStot).*10^(-3)))
legend('total mining','official mining','illegal mining in
China','mining need, high demand scenario','mining need, low demand
scenario')
legend ('Location','northwest')
title('Total annual Nd mining need')
set(gca,'XGrid','off','YGrid','on')
ylabel('Nd (kt)')
hold off

%without behavioural change
y = Ndproduction;
plot(x,y.*10^(-3))
hold on
%rec pot high
%plot(x,(recpotEVlow + recpotLDStot).*10^(-3),'LineStyle','--')
%demand high - recpot
plot(x,(NdEV(4,1:end).*10^(-3)+winddemandtot(3,1:end).*10^(-3)-
(recpotEVhighn + recpotHDStot).*10^(-3)))
plot(x,(NdEV(2,1:end).*10^(-3)+winddemandtot(1,1:end).*10^(-3)-
(recpotEVlown + recpotLDStot).*10^(-3)))
legend('total mining','official mining','illegal mining in
China','mining need, high demand scenario','mining need, low demand
scenario')
legend ('Location','northwest')
title('Annual Nd mining need')
set(gca,'XGrid','off','YGrid','on')
ylabel('Nd (kt)')
hold off
%%

%combined
%production
y = Ndproduction;
plot(x,y.*10^(-3))
hold on
%with behavioural change
plot(x,(NdEV(3,1:end).*10^(-3)+winddemandtot(3,1:end).*10^(-3)-
(recpotEVhigh + recpotHDStot).*10^(-3)),'LineStyle','-
','Color',[0.4940 0.1840 0.5560])
plot(x,(NdEV(1,1:end).*10^(-3)+winddemandtot(1,1:end).*10^(-3)-
(recpotEVlow + recpotLDStot).*10^(-3)),'LineStyle','-
','Color',[0.4660 0.6740 0.1880])
%without behavioural change
plot(x,(NdEV(4,1:end).*10^(-3)+winddemandtot(3,1:end).*10^(-3)-
(recpotEVhighn + recpotHDStot).*10^(-3)),'LineStyle','--
','Color',[0.4940 0.1840 0.5560])
plot(x,(NdEV(2,1:end).*10^(-3)+winddemandtot(1,1:end).*10^(-3)-
(recpotEVlown + recpotLDStot).*10^(-3)),'LineStyle','--
','Color',[0.4660 0.6740 0.1880])
legend('total mining','official mining','illegal mining in
China','mining need, high demand scenario','mining need, low demand
scenario')
legend ('Location','northwest')
title('Annual Nd mining need')
set(gca,'XGrid','off','YGrid','on')
ylabel('Nd (kt)')
```

```
hold off
%% Nd demand including other uses
%%
Ndotherw = [3185833047 33511 34048 33648 33501 34508 34763 34880
      34983 34923 34273 34068 33886 33759 34500 35250 36000 36750
      37500 38250 39000 39750 40500 41250 42000 42750 43500 44250
      45000];
Ndotherwo = [33684     34344 35031 35743 35468 35398 36431 36664
      36709 36690 36406 35473 34945 34366 33765 34500 35250 36000
      36750 37500 38250 39000 39750 40500 41250 42000 42750 43500
      44250 45000];
Ndotherwnet = Ndotherw .*0.5;   %assuming 50% of demand covered
from recycling
Ndotherwonet = Ndotherwo .*0.5; %same
%plot
%combined
%production
y = Ndproduction;
plot(x,y.*10^(-3))
hold on
%with behavioural change
plot(x,(Ndotherwnet.*10^(-3) + NdEV(3,1:end).*10^(-
3)+winddemandtot(3,1:end).*10^(-3)-(recpotEVhigh +
recpotHDStot).*10^(-3)),'LineStyle','-','Color',[0.4940 0.1840
0.5560])
plot(x,(Ndotherwnet.*10^(-3) + NdEV(1,1:end).*10^(-
3)+winddemandtot(1,1:end).*10^(-3)-(recpotEVlow +
recpotLDStot).*10^(-3)),'LineStyle','-','Color',[0.4660 0.6740
0.1880])
%without behavioural change
plot(x,(Ndotherwonet.*10^(-3) + NdEV(4,1:end).*10^(-
3)+winddemandtot(3,1:end).*10^(-3)-(recpotEVhighn +
recpotHDStot).*10^(-3)),'LineStyle','--','Color',[0.4940 0.1840
0.5560])
plot(x,(Ndotherwonet.*10^(-3) + NdEV(2,1:end).*10^(-
3)+winddemandtot(1,1:end).*10^(-3)-(recpotEVlown +
recpotLDStot).*10^(-3)),'LineStyle','--','Color',[0.4660 0.6740
0.1880])
legend('total mining','official mining','illegal mining in
China','mining need, high demand scenario','mining need, low demand
scenario')
legend ('Location','northwest')
title('Annual Nd mining need')
set(gca,'XGrid','off','YGrid','on')
ylabel('Nd (kt)')
hold off

%demand vs supply
y = Ndproduction;
plot(x,y.*10^(-3))
hold on
%with behavioural change
plot(x,(Ndotherw.*10^(-3) + NdEV(3,1:end).*10^(-
3)+winddemandtot(3,1:end).*10^(-3)),'LineStyle','-','Color',[0.4940
0.1840 0.5560])
plot(x,(Ndotherw.*10^(-3) + NdEV(1,1:end).*10^(-
3)+winddemandtot(1,1:end).*10^(-3)),'LineStyle','-','Color',[0.4660
0.6740 0.1880])
```

```
%without behavioural change
plot(x,(Ndotherwo.*10^(-3) + NdEV(4,1:end).*10^(-
3)+winddemandtot(3,1:end).*10^(-3)),'LineStyle','--
','Color',[0.4940 0.1840 0.5560])
plot(x,(Ndotherwo.*10^(-3) + NdEV(2,1:end).*10^(-
3)+winddemandtot(1,1:end).*10^(-3)),'LineStyle','--
','Color',[0.4660 0.6740 0.1880])
legend('total mining','official mining','illegal mining in
China','mining need, high demand scenario','mining need, low demand
scenario')
legend ('Location','northwest')
title('Annual Nd demand vs mining')
set(gca,'XGrid','off','YGrid','on')
ylabel('Nd (kt)')
hold off
```