



UNIVERSIDAD PONTIFICIA COMILLAS
ESCUELA TÉCNICA SUPERIOR DE INGENIERÍA (ICAI)

OFFICIAL MASTER'S DEGREE IN THE
ELECTRIC POWER INDUSTRY

Master's Thesis

**ASSESSING MINERAL DEMAND AND
CONSTRAINTS IN THE ENERGY
TRANSITION**

Author: Alvaro Ruiz del Tiempo

Supervisor: Javier Revuelta

Co-Supervisor:

Madrid, July 2024

Master's Thesis Presentation Authorization

THE STUDENT:

Alvaro Ruiz del Tiempo



Signed:

Date: 09 / 07 / 2024

THE SUPERVISOR:

Javier Revuelta



Signed:

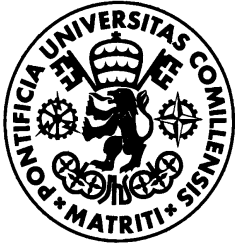
15/07/2024
Date: / /

Authorization of the Master's Thesis Coordinator

Dr. Luis Olmos Camacho

Signed:

Date: / /



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Abstract

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Author: Alvaro Ruiz del Tiempo

Director: Javier Revuelta

Entity: AFRY & ICAI – Universidad Pontificia Comillas

This project analyzes the demand for key minerals essential for the Energy Transition, considering various scenarios and public projections related to renewable energy development and electric vehicles. It estimates mineral production capacities to assess whether they can meet future demand, identifying which minerals may pose risks to the progress of decarbonizing the energy and transportation sectors.

Key words: Energy Transition, Mineral Demand and Supply, Renewable Energy, Electric Vehicles, Mining Industry

Introduction

The global shift towards sustainable and renewable technologies is essential to address climate change and reduce greenhouse gas emissions. However, this transition also impacts the natural resources required for these technologies. This Master's Thesis examines the increasing demand for key minerals, such as lithium and cobalt, which are vital for renewable technologies and electric vehicle batteries. It explores various scenarios to project mineral requirements up to 2050, highlighting potential supply limitations. The study underscores the challenges posed by the growing need for minerals, including environmental and social impacts of extraction. Conversely, it also identifies opportunities for innovation in developing more mineral-efficient technologies and promoting sustainable extraction practices. This analysis aims to provide a comprehensive understanding of the mineral needs for the Energy Transition and the associated challenges and opportunities.

Model Description

To advance the Master's Thesis and meet its objectives, various tasks have been proposed. These include examining official policies and conducting scenario analyses to gauge technology penetration rates, assessing mineral composition and intensity, and estimating base mineral demand using global production and refining data. Mineral demand will be categorized into base, energy, hydrogen, and transportation types, with annual capacity growth and aggregate demand analyzed. Refined mineral data modeling will project base demand to 2050, incorporating historical data and socioeconomic variables. Sector-specific mineral demand will be assessed, including the impact of sub-technologies, energy requirements, and CO₂ emissions. Comprehensive statistics on production, refining, and reserves will be compiled, alongside investigations into recycling rates, mineral lifespan, and ore purity. Historical supply data and future investments will be modeled using Holt's, ARIMA, or Hubbert curves, with a user interface developed for recycling efficiency projections and comparative analyses conducted to align future supply with escalating demand.

Results

Starting with an analysis of mineral intensity by technology and projections for installed capacity in line with international decarbonization policies for 2050, this study has projected significant increases in the demand for key minerals such as cobalt, lithium, nickel, and copper. These minerals are expected to see demand surge by over 15 times in the most extreme net zero emissions scenarios by 2050, underscoring their critical role in renewable energy technologies and electric vehicles. Analyzing current mining production capacity under linear and exponential trends, the study found that a linear increase would quickly decouple supply from demand, creating substantial gaps. In contrast, exponential projections using Hubbert curves indicated potential peak production times but still highlighted the fundamental role of recycling in maintaining supply levels close to demand. The study also linked mineral demand to the energy required for extraction and associated CO₂ emissions, revealing a hidden carbon footprint often overlooked in current energy policies. As mines are increasingly exploited, the energy needed for extraction rises, leading to faster energy consumption growth

compared to mineral demand growth. These findings indicate that under worst-case recycling and net zero emissions scenarios for 2050, mining production would become a bottleneck, hindering decarbonization efforts. Even with high technological progress in recycling, critical minerals like copper, cobalt, nickel, lead, and rare earth elements remain constrained in meeting projected demand.

Conclusions

In conclusion, energy policies must integrate strategies addressing the entire mineral supply chain, from extraction to recycling, with a focus on advancing extraction technologies and enhancing recycling processes. Policymakers should mitigate mining's environmental impacts and CO₂ emissions. Future studies should monitor investment in key mineral deposits, balancing market prices with the costs of exploration and exploitation. Investing in and developing more mineral-efficient technologies is crucial. Economic signals, driven by market dynamics, are essential for guiding development and decision-making, aligning with international sustainability objectives.

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1. Introduction

The Energy Transition to greater use of sustainable and renewable technologies has become a global priority to meet the challenges of climate change and the pressure to reduce greenhouse gas emissions. However, the Energy Transition involves not only the deployment of new renewable technologies but also understanding the impact it will have on the planet's existing natural resources required for their implementation. In this context, it is essential to analyze the increase in demand on certain minerals whose intensity in these renewable technologies becomes highly relevant and thus, it is possible to know the associated limitations that could appear in the short/medium term. This Master Thesis seeks to address different scenarios to understand what the mineral requirements will be considering the greater or lesser penetration of different technologies to 2050 in order to understand the importance of minerals in the Energy Transition to the challenges and opportunities facing its extraction and supply.

Today, minerals play a key role in the transition to a more sustainable energy sector. Several cases can be quickly identified, from the lithium used in electric vehicle batteries to the cobalt needed in energy storage systems; these resources are essential for the manufacture of key technologies over the next 5-30 years. Hence, the growing demand for minerals in the context of the Energy Transition presents several challenges and opportunities. On the one hand, the increase in the production of sustainable technologies leads to a greater need for minerals, which may result in additional pressures on natural resources and possible environmental and social impacts associated with their extraction. On the other hand, this demand also creates opportunities for innovation and the development of more mineral-efficient technologies, as well as for the promotion of more sustainable and responsible extraction practices.

Although the relevance of minerals in this Energy Transition is well known, supply and extraction are not without limitations and challenges. Firstly, many of the minerals identified as critical, as their extraction is concentrated in a limited number of countries, can generate dependence and vulnerability in terms of security of supply. In addition, they are extracted from underdeveloped countries where workers' conditions are

inadequate, and whose extraction may be associated with negative environmental impacts, such as soil degradation, water pollution and loss of biodiversity, which poses significant challenges in terms of sustainability and social responsibility.

1.1. Motivation

This Master's Thesis is fueled by the global imperative to decarbonize the electricity sector and the necessity to proactively address potential shortages of essential metals that could hinder the progress of the Energy Transition. It seeks to delve into the intricate interplay between mineral requirements and the seamless integration of renewable energy sources, all while contributing to broader sustainability objectives on a worldwide scale. Hence, the main motivations driving this Master's Thesis are:

- Global transition towards RES represents a paradigm shift in the energy landscape, driven by concerns over climate change and energy security. By analyzing the drivers behind this transition, such as evolving consumer preferences, and tech advancements, gaining insights into the scale and scope of mineral demand for the Energy Transition.
- Across the globe, governments are formulating comprehensive Energy Transition plans aimed at achieving ambitious renewable energy targets and reducing greenhouse gas emissions. These plans, exemplified by initiatives like Spain's PNIEC, outline specific measures and targets to be achieved within defined timeframes.
- By staying abreast of the latest developments in energy technology and conducting thorough assessments of emerging trends, and as consumer demand for EVs, heat electrification & electrolyzers continues to rise, opportunities and challenges can be identified associated with evolving mineral requirements.

1.2. Objectives

The objectives to be encompassed by this endeavor are outlined as follows:

- Comprehensive analysis to quantify the specific mineral requirements associated with various RE technologies and energy storage systems – Examining the

composition of solar panels, wind turbines, and ESS, as well as their respective market shares and growth trajectories, estimating the magnitude of mineral demand for each technology.

- Critical examination of distinct sets of scenarios governing mineral demand projections within the context of the Energy Transition: official forecasts provided by governmental bodies and independent assessments developed – illuminate disparities, similarities, and implications of divergent perspectives on mineral demand and supply requirements.
- Comprehensive assessment of energy consumption associated with mining activities, with a focus on enhancing sustainability and mitigating environmental impacts.
- Comprehensive assessment of mineral production capacities under various growth trends, and comparison with demand projections.

1.3. Alignment with the Sustainable Development Goals

The Sustainable Development Goals (SDGs) are a set of 17 global targets set by the United Nations in its 2030 Agenda, designed to address the most pressing challenges facing humanity and promote a more prosperous, equitable and sustainable future for all. These goals cover a wide range of areas, from eradicating poverty and hunger to climate action. In the context of this MA Master Thesis, the SDGs provide a comprehensive framework for understanding and addressing the challenges associated with mineral demand and Energy Transition. Specifically, the analysis of critical mineral demand and supply shortages for the transition to more sustainable energy sources aligns with several SDGs, including:

- **SDG 7 Affordable and Clean Energy:** This goal seeks to ensure access to affordable, reliable, sustainable and modern energy for all. The project contributes to this goal by analyzing how the availability of critical minerals impacts the transition to cleaner and renewable energy sources.
- **SDG 9 Industry, Innovation and Infrastructure:** The Energy Transition propels the advancement of novel technologies, including electric vehicles and hydrogen electrolyzers, aimed at curtailing CO₂ emissions, thereby escalating the demand

for minerals. Within this framework, comprehending technological advancements becomes imperative to optimize mineral recycling and devise innovative machinery to diminish energy consumption in their extraction processes.

- **SDG 12 Responsible Production and Consumption:** By investigating the demand for minerals and their impact on the Energy Transition, the project addresses the need to promote sustainable production and consumption patterns, minimizing the use of natural resources and reducing the environmental impacts associated with their extraction and processing.
- **SDG 13 Climate Action:** The transition to more sustainable energy sources is crucial to mitigate climate change and its adverse effects. The project contributes to this goal by examining how the availability of critical minerals can affect the speed and effectiveness of this transition.

2. State of Art

2.1. Preliminary Work

The literature on mineral demand and supply, especially in the context of the Energy Transition, is extensive and multifaceted. Key areas of focus include projections of mineral requirements for renewable energy technologies, analysis of supply constraints, and the potential for recycling and material substitution. Below is a survey of the relevant literature.

- "Global Critical Minerals Outlook 2024" (IEA) provides a comprehensive overview of projected mineral demand under various scenarios such as the Stated Policies Scenario, the Announced Pledges Scenario, and the Net Zero Emissions by 2050 Scenario. The report highlights the significant increase in demand for minerals like copper, lithium, nickel, cobalt, and rare earth elements driven by clean energy technologies. It also discusses the potential supply shortfalls for minerals like copper and lithium due to limited new project developments and declining ore quality.
- Alicia Valero's work emphasizes the critical materials required for renewable technologies and identifies potential bottlenecks that could hinder the Energy Transition. This includes the high demand for rare earth elements, lithium, and cobalt. Increasing recycling rates and material efficiency are critical to mitigating supply risks. Valero et al. discuss the potential for recycling to play a significant role in meeting future mineral demand, particularly for materials like lithium from end-of-life batteries. In the supply side, Valero et al. apply Hubbert peak models and dynamic market simulations to non-fuel minerals, indicating that the supply of certain minerals could peak and decline, affecting their long-term availability.
 - "Global material requirements for the Energy Transition. An exergy flow analysis of decarbonization pathways"
 - "Límites minerales de la transición energética"
 - "Material bottlenecks in the future development of green technologies"

- “Assessing maximum production peak and resource availability of non-fuel mineral resources: Analyzing the influence of extractable global resources”
- Emmanuel Aramendia: “Global energy consumption of the mineral mining industry: Exploring the historical perspective and future pathways to 2060”

2.2. Initial Conclusions & Present Gaps

The reviewed literature unequivocally indicates that the demand for critical minerals is set to rise substantially as the world transitions towards renewable energy technologies. This surge is driven primarily by the increased production and deployment of technologies such as electric vehicles, wind turbines, and solar panels, which require significant amounts of minerals like lithium, cobalt, nickel, and rare earth elements. For instance, the IEA projects a steep increase in the demand for these minerals under various Energy Transition scenarios. This rising demand underscores the importance of critical minerals in the global effort to combat climate change and achieve net-zero emissions by 2050.

Supply risks associated with critical minerals are multifaceted, encompassing geographical concentration, geopolitical tensions, and environmental sustainability. Many of these minerals are concentrated in a few countries, leading to potential supply disruptions due to geopolitical instability. For example, a significant portion of the world's cobalt supply comes from the Democratic Republic of Congo, a region known for political instability and ethical concerns regarding mining practices. The literature emphasizes the need for diversified supply sources to mitigate these risks. Sustainable mining practices are also critical to ensure that the environmental impact of extracting these minerals is minimized, thereby aligning mineral supply chains with broader sustainability goals.

Recycling emerges as a pivotal strategy in addressing the supply-demand imbalance of critical minerals. By recovering valuable materials from end-of-life products, recycling can significantly reduce the need for primary extraction and alleviate some of the supply constraints. Valero et al. highlight the importance of improving

recycling rates for materials like lithium and cobalt, particularly from spent batteries. However, current recycling rates are far from adequate. For instance, the United Nations Environment Programme reports that the recycling rates for many essential minerals remain below 1%. Enhancing recycling infrastructure and technologies is therefore crucial to meeting future mineral demand sustainably.

Material substitution is another important avenue explored in the literature to address the supply risks of critical minerals. Research into alternative materials that can replace scarce or geopolitically sensitive minerals is ongoing. For example, advancements in battery technology are exploring the use of manganese and other more abundant elements as substitutes for cobalt. Such innovations not only reduce dependency on critical minerals but also potentially lower the environmental and ethical impacts associated with their extraction. However, the commercialization and market acceptance of these substitutes remain a challenge that needs to be addressed through continued research and development.

On the other hand, some gaps can be identified in the literature analyzed given the high uncertainty that exists with the technological and economic development that the energy sector will experience. One of the most pressing gaps identified in the literature is the inadequacy of current recycling infrastructure for critical minerals. While the potential for recycling to mitigate supply risks is well recognized, the technologies and systems required to achieve high recovery rates are not yet fully developed. There is a clear need for significant investment in recycling facilities and research into more efficient and cost-effective recycling processes. For instance, improving the separation and recovery of rare earth elements from electronic waste could drastically reduce the reliance on primary mining. Furthermore, from a more technological perspective, while material substitution offers a promising solution to the supply risks of critical minerals, the research in this area is still in its nascent stages. There is a need for a more concerted effort to identify and develop viable substitutes for critical minerals used in renewable energy technologies.

Regarding geopolitical challenges, the concentration of critical mineral production in a limited number of countries poses significant geopolitical risks. Countries that dominate the supply chain for these minerals can exert considerable influence on

global markets, potentially leading to supply disruptions. The literature calls for policies that promote supply diversification and the establishment of strategic reserves to buffer against such disruptions. Additionally, the environmental impact of mining activities, particularly in regions with lax environmental regulations, remains a major concern. Future research should focus on developing sustainable mining practices that minimize ecological damage and ensure the well-being of local communities.

Ensuring the sustainability of mineral supply chains is another critical gap highlighted in the literature. Current supply chain practices often fail to account for the full environmental and social impacts of mineral extraction and processing. Future research should focus on developing comprehensive sustainability metrics that can guide the management of mineral supply chains. Moreover, this gap could be overcome through the integration of circular economy principles, this involves designing products for durability, reparability, and recyclability, thereby extending their lifecycle and reducing the need for virgin materials.

3. Problem Setting

3.1. Problem Description

The analysis of the demand and expectation or requirement of mineral supply to cope with the penetration of renewable and sustainable technologies is essential to understand whether the world will be able to achieve the targets set for decarbonization of the energy sector and achieve CO₂ emission reductions by 2050, even considering a scenario of net zero emissions. To develop a comprehensive analysis it is necessary, on the one hand, the use of models and tools that allow predicting future variables considering the historical development and socio-economic components at global level and on the other hand, databases containing accurate information on the historical development of the mining industry and the different target scenarios to meet the 2030 agenda and 2050 targets (Stated Energy Policies, Announced Policies, Net Zero, Free Scenario).

These historical models and data sets will enable to predict and project future demand for critical minerals. This, in turn, allows to draw insightful conclusions regarding the necessary capacity development and technological advancements required by the mining industry to ensure that the supply can meet the demand, always mindful of the available resources and reserves on the Earth.

The International Energy Agency (IEA) provides projections of global installed capacity by technology in the energy sector through its World Energy Outlook (updated to the 2023 version). These data serve as a starting point, from which mineral intensity by technology and categorize demand can be analyzed into the following segments:

- Base Demand: Reflects historical demand, correlated with socioeconomic variables.
- Energy Demand: Accounts for the penetration of renewable and sustainable energy plants required in the Energy Transition, such as Solar, Wind, Biomass, Geothermal, CSP, new transmission and distribution networks, segmented by technology for precise mineral analysis.

- Transportation Demand: Reflects the penetration of electric vehicles with a standard battery capacity of 65-75 kWh, segmented by battery technology due to their mineral concentration.
- Hydrogen Demand: Addresses the requirements of hydrogen electrolyzers within the energy sector, segmented by technology.
- Nuclear Demand: Given its non-renewable nature and significant influence on the political-energy landscape, nuclear demand plays a crucial role in CO2 emission reduction strategies, allowing for additional scenario planning.

All these predictions will be based on in-depth research to ensure the best fitting of initial data, resulting in reliable estimates. These estimates will serve as a basis for drawing meaningful conclusions about potential limitations within the energy sector's supply chain. Historical consumption data for each mineral can be derived from global refined metal production, representing the final result of mineral production and recycling within the supply chain, considering mineral lifespan and various recycling capacity development projections.

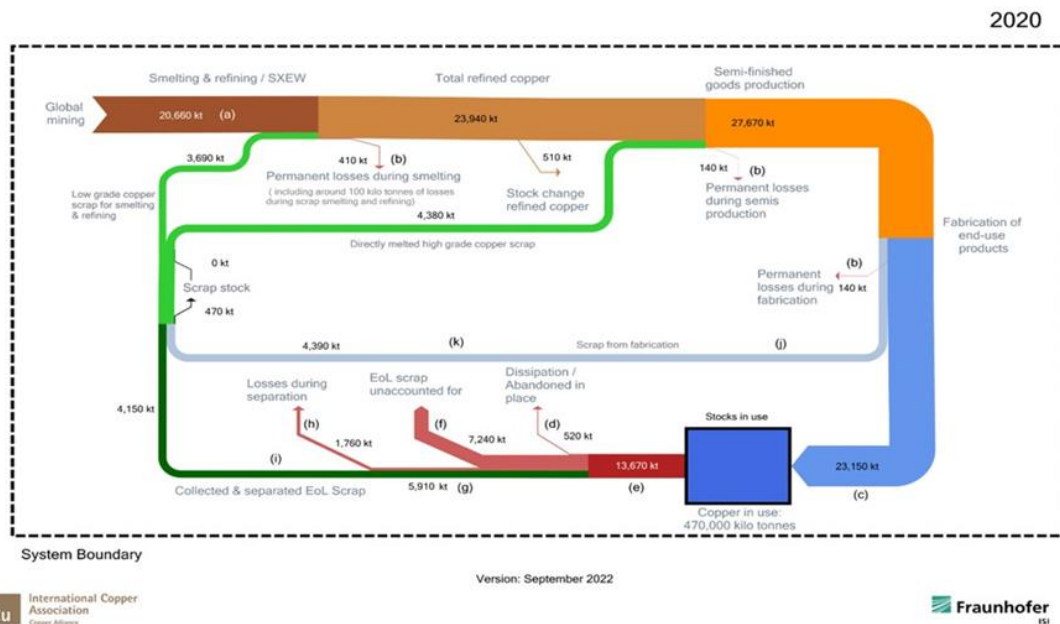


Figure 3.1. Copper Supply Chain. Source: International Copper Association

For future estimations, among various projection methods, linear regressions using Excel's Data Analysis tool have been employed to project the base demand for each

mineral, considering socioeconomic variables such as GDP, world population, year, urbanization level, and economic growth.

The evaluation of 15 models, combining different variables with their natural values or logarithmic transformations, has been conducted using an 80% training batch of known data and a 20% test batch to analyze estimation errors through Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Error (ME), with subsequent checks to ensure future results stability. This evaluation process will be applied to each mineral within the study. Once the actual demand is known, it will be compared with the projected supply capacity. Initially, future supply will be projected linearly using time series models such as Holt's double exponential and first-order ARIMA models, and ultimately validated through Hubbert curves.

3.2. Work Methodology

To advance the Master's Thesis and endeavor toward fulfilling the initially established objectives, the following tasks have been proposed for execution:

- Task 1: These include examining official policies that govern the advancement of new technologies and conducting a scenario analysis to gauge the varying penetration rates of specific technologies. Additionally, the mineral composition of each technology will be thoroughly examined, with a focus on quantitatively assessing their intensity, measured in kg/MW or kg/unit. Furthermore, the estimation of the base demand for each mineral will be conducted, leveraging comprehensive global production and refining data as benchmarks.
- Task 2: Firstly, mineral demand will be categorized into four distinct types: base, energy, hydrogen, and transportation demand. Secondly, the annual capacity growth per technology, as per the selected scenario, will be analyzed alongside the aggregate mineral demand, with certain periods extrapolated through linear methods. Additionally, a user-friendly interface control panel will be developed to facilitate the adjustment of penetration levels for sub-technologies within solar, wind, battery, and electrolyzer, ensuring ease of use and accessibility for stakeholders and researchers alike.

- Task 3: Refined mineral data modelling will be utilized to extrapolate the base demand trajectory up to 2050 on a global scale, providing valuable insights into future mineral requirements. Secondly, a learning batch spanning until 2009-10 will be employed for training purposes, followed by a testing batch extending until 2020, with existing known energy demands factored in, enhancing the accuracy of predictive models. Additionally, a correlation study will be conducted to examine the relationship between base demand and various socioeconomic variables, including GDP, GDP per capita, population, urbanization rates, and time factors, shedding light on the complex interplay between mineral demand and broader socio-economic trends.
- Task 4: In-depth assessment of mineral demand across sectors will be conducted, scrutinizing current requirements and projecting future growth patterns to inform mining requisites, thereby providing valuable insights into evolving resource needs. Secondly, the influence of heightened penetration rates of select sub-technologies, such as evolving trends within various battery types, will be analyzed to understand their impact on overall demand dynamics, facilitating a nuanced understanding of technological shifts. Additionally, energy requirements will be quantified in terms of barrels of oil equivalent, and associated CO2 emissions necessary to meet the escalating mineral demand sustainably will be assessed, contributing to a holistic evaluation of environmental implications and sustainability considerations.
- Task 5: Extensive compilation of annual production, refining, and reserve statistics for each ore type will be conducted, providing a comprehensive overview of resource availability. Secondly, an investigation into the average recycling rates of individual minerals and their projected lifespan within the value chain will be undertaken, exploring opportunities for potential reutilization and sustainability. Additionally, an assessment of the purity grade inherent in existing ore deposits will be conducted, coupled with considerations regarding investments in future deposits to ascertain quality and viability, contributing to informed decision-making in resource allocation and extraction strategies.

- Task 6: Historical supply data alongside future investments will be modeled using Holts double exponential, ARIMA, or Hubbert curves, enabling an in-depth analysis of the dynamics of each mineral to inform strategic planning. Secondly, an intuitive user interface control panel will be developed, facilitating the incorporation of enhanced mineral recycling efficiency projections up to 2050, fostering sustainable resource management. Additionally, a comparative analysis will be conducted to assess whether the anticipated future supply capacity will align with the escalating demand for minerals essential to the Energy Transition, providing critical insights into potential supply-demand imbalances and informing policy and investment decisions in the energy sector.

Project will progress through research stages, followed by forecast modelling, analysis, and comparison of results over a 15-week timeline:

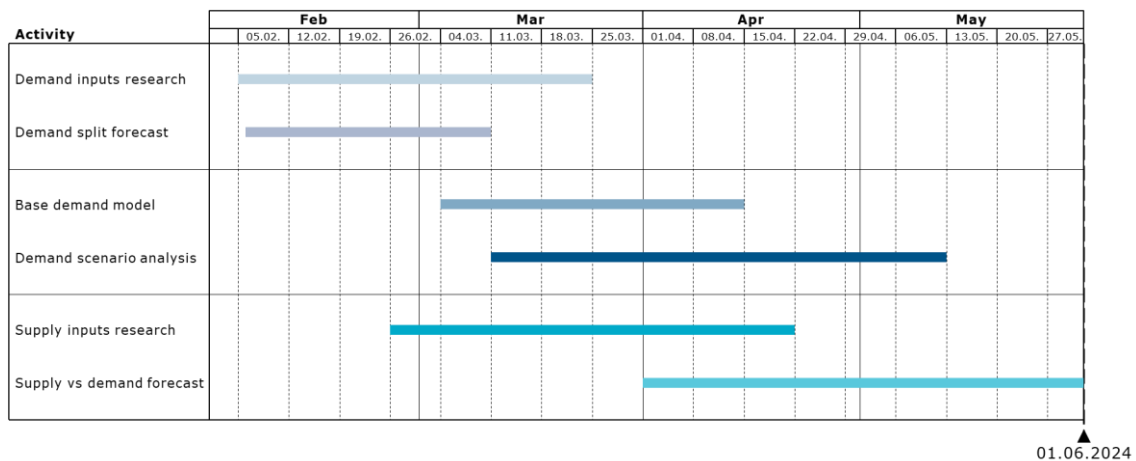


Figure 3.2. Gantt Chart Master's Thesis progress. Source: Own development

3.3. Resources to use

The external resources that will be used for the Master's thesis are:

- R-Studio: ARIMA model suitability analysis
- Microsoft Office:
 - o Excel: Modeling Scenarios
 - o Word: Thesis document
 - o PowerPoint: Presentation

- Databases as:
 - World Energy Outlook – IEA
 - USGS Mining Database
 - British Geological Survey Database
 - S&P Global Mining Activity Database
- Other AFRY resources

4. Proposed Method

To meet the objectives of this thesis, a predictive model for the demand and supply of minerals over the coming years will be developed. This model will employ a methodology that facilitates the parallel analysis of both aspects using mathematical techniques, supported by existing research on the significance of minerals in the Energy Transition. The projections will inherently contain a degree of uncertainty due to the assumptions integrated into the model and the potential errors in the mathematical approaches used. Rather than aiming for highly accurate predictions, this thesis seeks to qualitatively illustrate the current state of the mining sector and its critical role in the Energy Transition, emphasizing the sector's importance in achieving an emission-free energy future.

Among the numerous minerals for which data has been collected to analyze various technologies, only ten will be comprehensively studied. These minerals are deemed crucial for sustainable energy development, and their scarcity could hinder decarbonization efforts, necessitating the exploration of alternative solutions:

- Aluminum
- Cadmium
- Cobalt
- Copper
- Iron
- Lead
- Lithium
- Nickle
- REE
- Vanadium
- Zinc

The following sections will detail the methodology employed for analyzing the demand and supply of minerals. Specifically, the coefficients and result tables for the predictive models concerning copper will be developed and presented. This

comprehensive approach ensures that the primary focus remains on copper, while still offering complete data for other minerals to support the overall analysis.

4.1. Demand Forecast

Before delving into the development of the claim, it is important to note that three different scenarios have been studied:

- **Stated Policies Scenario:** Also known as STEPS, represents a conservative and pragmatic approach to future energy projections, grounded in the current policy landscape. It encompasses all existing policies and measures that have been formally adopted or are in the process of being implemented by governments around the world. This scenario assumes that no significant new policies will be introduced beyond those already in place, thus providing a baseline projection based on the continuation of current trajectories. STEPS includes the expected advancements in technology and market trends that are already underway, such as ongoing improvements in energy efficiency and the gradual deployment of renewable energy technologies. The scenario offers a detailed analysis of how energy demand and supply are anticipated to evolve under these existing policies, considering different energy sources like fossil fuels, renewables, and nuclear energy, and their respective roles in the global energy mix. The implications of STEPS highlight that the Energy Transition towards lower-carbon sources is likely to proceed at a moderate pace. While there will be significant growth in renewable energy and enhancements in energy efficiency, fossil fuels are projected to continue playing a substantial role in the global energy landscape. As a result, global carbon emissions are expected to rise, albeit at a slower rate than in previous decades, indicating a gap between current policies and the more aggressive measures required for substantial emissions reductions. The scenario identifies the investment needed to maintain and expand energy infrastructure under the existing policy frameworks, emphasizing the importance of continued investment in renewable energy, energy efficiency, and grid modernization, alongside the ongoing development of fossil fuel resources. Energy security remains a critical concern in STEPS, as fossil fuels continue to dominate,

underscoring the need for sustained investment in supply diversification and resilience to ensure stable and reliable energy access. Moreover, while some improvements in air quality and reductions in pollutants are anticipated, more stringent measures will be necessary to address broader environmental challenges, such as climate change and biodiversity loss.

- **Announced Pledges Scenario:** Also known as APS, offers a more optimistic and forward-looking projection of the energy sector by considering both the policies currently in place and those that have been announced and are expected to be implemented in the near future. This scenario reflects a higher level of policy ambition, as it anticipates the enactment of additional measures aimed at accelerating the Energy Transition and addressing environmental challenges. APS includes proposed legislation, regulatory changes, and international commitments that governments have publicly declared but may not yet be fully implemented. This scenario accounts for the potential impact of these forthcoming policy measures on the energy landscape. It takes into consideration expected advancements in technology and market innovations driven by the announced policies, such as more rapid deployment of renewable energy technologies, improvements in energy storage, and the development of new low-carbon technologies. APS provides detailed projections of energy demand and supply dynamics under the influence of these announced policies, reflecting potential shifts in energy consumption patterns and the increased penetration of clean energy sources. The implications of APS highlight that the Energy Transition is expected to gain significant momentum, with a more pronounced shift towards renewable energy sources and substantial improvements in energy efficiency. The scenario suggests that the announced policies will drive considerable reductions in the use of fossil fuels and increase the share of clean energy in the global energy mix. Global carbon emissions are projected to peak and begin to decline under APS, indicating progress towards achieving international climate targets, although further measures may still be necessary to reach the most ambitious goals. The scenario identifies the investment required to support the implementation of the announced policies, including investments in renewable

energy infrastructure, energy efficiency measures, and the development of new low-carbon technologies. APS also emphasizes the importance of enhancing energy security and resilience in the context of a changing energy landscape, highlighting the need for continued diversification of energy sources and the development of robust energy systems to ensure reliable energy access. The scenario indicates that the announced policies will lead to significant environmental and social benefits, including improved air quality, reduced greenhouse gas emissions, and enhanced public health. Additionally, APS underscores the potential for job creation and economic growth in the clean energy sector.

- Net Zero Scenario: Also known as NZS, represents an ambitious and transformative pathway in which global efforts are aligned to achieve net-zero greenhouse gas emissions by a specific target year, often 2050. This scenario requires comprehensive and aggressive policy measures, rapid technological advancements, and significant shifts in energy production and consumption patterns. NZS envisions a world where strong global commitments to achieving net-zero emissions are in place, necessitating the adoption of stringent policies aimed at reducing greenhouse gas emissions across all sectors of the economy. The scenario assumes rapid advancements in clean energy technologies, including renewable energy, energy storage, carbon capture and storage (CCS), and hydrogen production, with these technologies being deployed at scale to achieve deep decarbonization. NZS also anticipates significant changes in energy consumption patterns and societal behaviors, such as increased energy efficiency, shifts towards sustainable transportation modes, and changes in industrial processes to reduce carbon footprints. The scenario outlines a comprehensive transformation of the energy system, with a substantial increase in the share of renewable energy sources, a phase-out of unabated fossil fuels, and the development of resilient and flexible energy infrastructure. The implications of NZS underscore a rapid and deep decarbonization pathway, characterized by a significant reduction in fossil fuel use and a corresponding increase in renewable energy generation and energy efficiency. Global carbon emissions are projected

to decline rapidly under NZS, reaching net-zero by the target year. This scenario emphasizes the importance of early and sustained policy action to achieve the necessary emissions reductions. The scenario identifies substantial investment needs to support the transition to a net-zero energy system, including investments in renewable energy infrastructure, energy efficiency measures, and the development of new low-carbon technologies. NZS also highlights the importance of enhancing energy security and resilience through the diversification of energy sources and the development of robust energy infrastructure. The scenario indicates that achieving net-zero emissions will result in significant environmental and social benefits, such as improved air quality, reduced greenhouse gas emissions, and enhanced public health. Additionally, NZS underscores the potential for job creation and economic growth in the clean energy sector, as well as the importance of ensuring a just and equitable transition for all communities.

After describing the scenarios that form the foundation for predicting mineral demand under the accelerated development of renewable technologies and the proliferation of electric vehicles, the step-by-step methodology will be outlined.

4.1.1. Demand Inputs

The first step in projecting future mineral demand involves understanding the historical data and the targets set by global institutions to meet the objectives of the different scenarios. As outlined in the previous section, demand has been categorized into five segments related to socioeconomic growth, the development of the electric vehicle fleet, and the new renewable capacity installed in the global energy mix. Data on the current installed capacity and future targets for each energy mix scenario were obtained from the World Electricity Outlook 2023, presented by the International Energy Agency. These values are displayed in the following tables:

Stated Policies Scenario (STEPS)							
Technology	2010	2021	2022	2030	2035	2040	2050
Solar PV	39	925	1,145	4,699	7,174	9,500	12,639
Wind	181	827	902	2,064	2,747	3,242	3,874

Hydro	1,027	1,360	1,392	1,571	1,681	1,801	2,028
Bioenergy	74	159	168	232	272	311	393
CSP	1	6	7	16	29	46	85
Geothermal	10	15	15	27	37	47	63
Marine	-	1	1	3	9	18	36
Nuclear	403	413	417	482	521	557	622
H2 & Ammonia	-	-	-	8	17	24	19
Coal	1,614	2,200	2,236	2,126	1,956	1,795	1,363
Natural Gas	1,389	1,854	1,875	2,071	2,139	2,185	2,259
Oil	436	426	423	301	269	236	178
Battery Storage	1	27	45	552	1,047	1,531	2,352

Table 1. Installed capacity in GW - Stated Policies Scenario. Source: IEA

Announced Pledges Scenario (APS)					
Technology	2022	2030	2035	2040	2050
Solar PV	3,629	9,786	14,426	18,893	25,368
Wind	1,145	5,377	8,648	11,787	16,041
Hydro	902	2,420	3,418	4,337	5,879
Bioenergy	1,392	1,620	1,804	1,991	2,304
CSP	7	29	86	165	295
Geothermal	15	34	51	67	100
Marine	1	5	12	23	44
Nuclear	417	497	587	677	769
H2 & Ammonia	-	31	134	174	195
Coal	2,236	2,036	1,749	1,474	911
Natural Gas	1,875	1,905	1,743	1,613	1,371
Oil	423	283	234	202	150
Battery Storage	45	725	1,377	2,029	3,121

Table 2. Installed capacity in GW - Announced Pledges Scenario. Source: IEA

Net Zero Scenario (NZS)					
Technology	2022	2030	2035	2040	2050
Solar PV	1,145	6,101	10,430	14,303	18,753
Wind	902	2,742	4,322	5,797	7,616
Hydro	1,392	1,765	2,054	2,313	2,612
Bioenergy	168	296	426	541	688

CSP	7	48	134	251	427
Geothermal	15	48	78	99	129
Marine	1	8	16	27	48
Nuclear	417	541	688	813	916
H2 & Ammonia	-	129	367	447	427
Coal	2,236	1,457	910	548	242
Natural Gas	1,875	1,746	1,402	1,088	611
Oil	423	220	141	75	39
Battery Storage	45	1,018	1,949	2,841	4,199

Table 3. Installed capacity in GW - Net Zero Scenario. Source: IEA

The projections for the global energy mix in intermediate years will be calculated using linear regression between the target years provided as inputs.

Even with the target energy mix for the Energy Transition established, understanding its impact on mineral requirements is essential. This impact is determined by the mineral intensity per technology, derived from various sources. This information will help identify which renewable technologies and electric vehicles demand more minerals or specific types of minerals. Although the data is presented for the year 2023, it will remain constant throughout the historical analysis. However, it is important to note that technological advancements may lead to a reduction in mineral requirements or a shift in the types of minerals used for the same technologies in the coming years.

Mineral Intensity (kg/MW)				
Technology	PV c-Si	PV CIGS	PV CdTe	Hydro
Aluminum	-	-	-	-
Cadmium	6.10	1.80	65.20	-
Chromium	-	-	-	96,000.00
Cobalt	-	-	-	-
Copper	4,177.50	19.00	42.80	-
Gallium	0.10	4.90	-	-
Germanium	-	-	-	-
Graphite	-	-	-	-
Indium	4.50	23.20	15.90	-
Iron	-	-	-	1,242,000.00

Lead	-	-	-	-
Lithium	-	-	-	-
Manganese	-	-	-	5,760.00
Molybdenum	-	94.30	100.50	-
Nickel	1.10	-	-	-
Phosphorus Rock	-	-	-	-
PGM	-	-	-	-
REE	-	-	-	-
Silicon	6,326.50	-	-	-
Silver	133.00	-	-	-
Tellurium	4.70	-	65.40	-
Tin	520.00	-	6.60	-
Tungsten	-	-	-	-
Vanadium	-	-	-	-
Zinc	-	85.80	-	-
Others	54.00	38.10	-	-

Mineral Intensity (kg/MW)				
Technology	CSP PT	CSP CRS	Offshore Wind	Onshore Wind
Aluminum	740.00	23.00	840.00	840.00
Cadmium	-	-	-	-
Chromium	2.20	3.70	525.00	470.00
Cobalt	-	-	-	-
Copper	3.20	1.40	8,000.00	2,900.00
Gallium	-	-	-	-
Germanium	-	-	-	-
Graphite	-	-	-	-
Indium	-	-	-	-
Iron	650,000.00	393,000.00	292,100.00	172,100.00
Lead	-	-	-	-
Lithium	-	-	-	-
Manganese	2.00	5.70	790.00	780.00
Molybdenum	200.00	56.00	109.00	99.00
Nickel	940.00	1.80	240.00	403.50
Phosphorus Rock	-	-	-	-

PGM	-	-	-	-
REE	-	-	197.33	97.33
Silicon	-	-	-	-
Silver	13.00	16.00	-	-
Tellurium	-	-	-	-
Tin	-	-	-	-
Tungsten	-	-	-	-
Vanadium	-	-	-	-
Zinc	650.00	1.40	5,500.00	5,500.00
Others	27.00	2.00	6.00	-

Mineral Intensity (kg/MW)				
Technology	Geothermal	Nuclear	Coal	Natural Gas
Aluminum	6,790.00	200.00	-	750.00
Cadmium	-	-	-	-
Chromium	200.00	2,190.00	308.00	48.34
Cobalt	-	-	201.46	1.80
Copper	2,440.00	1,473.00	1,150.00	1,100.00
Gallium	-	-	-	-
Germanium	-	-	-	-
Graphite	-	-	-	-
Indium	-	-	-	-
Iron	14,900.00	58,904.00	-	5,500.00
Lead	-	-	-	-
Lithium	-	-	-	-
Manganese	-	147.69	4.63	-
Molybdenum	-	70.80	66.25	-
Nickel	240.00	1,297.40	721.00	15.75
Phosphorus Rock	-	-	-	-
PGM	-	-	-	-
REE	-	0.50	-	-
Silicon	-	-	-	-
Silver	-	-	-	-
Tellurium	-	-	-	-
Tin	3.60	-	-	-

Tungsten	-	-	-	-
Vanadium	-	-	-	-
Zinc	110.00	-	-	-
Others	-	94.28	33.90	-

Mineral Intensity (kg/MW)				
Technology	H2 Alkaline	H2 PEM	H2 SOEC	Battery Storage
Aluminum	500.00	-	-	-
Cadmium	-	-	-	-
Chromium	-	-	-	-
Cobalt	-	-	-	37.30
Copper	-	-	-	2,200.00
Gallium	-	-	-	-
Germanium	-	-	-	-
Graphite	-	-	-	-
Indium	-	-	-	-
Iron	-	-	-	-
Lead	-	-	-	-
Lithium	-	-	-	404.50
Manganese	-	-	-	34.80
Molybdenum	-	-	-	-
Nickel	800.00	-	175.00	163.50
Phosphorus Rock	-	-	-	-
PGM	-	1.90	-	-
REE	-	-	25.00	-
Silicon	-	-	-	45.50
Silver	-	-	-	-
Tellurium	-	-	-	-
Tin	-	-	-	-
Tungsten	-	-	-	-
Vanadium	-	-	-	918.00
Zinc	-	-	-	-
Others	100.00	-	40.00	-

Table 4. Mineral Intensity in kg/MW. Source: IEA.

Mineral Intensity (kg/unit)				
Technology	BEV	PHEV	EV NMC	EV NCA
Aluminum	200.00	141.37	43.72	46.18
Cadmium	-	-	-	-
Chromium	6.03	6.51	-	-
Cobalt	9.33	2.71	15.28	6.52
Copper	150.00	59.17	25.88	23.42
Gallium	0.00	0.00	-	-
Germanium	0.00	0.00	-	-
Graphite	-	-	67.20	67.84
Indium	0.00	0.00	-	-
Iron	746.95	806.14	-	-
Lead	9.75	9.75	-	-
Lithium	7.71	2.24	9.40	7.59
Manganese	5.53	5.97	16.03	-
Molybdenum	0.26	0.26	-	-
Nickel	55.72	16.05	37.39	53.63
Phosphorus Rock	-	-	-	-
PGM	-	0.01	-	-
REE	0.90	0.69	-	-
Silicon	-	-	-	-
Silver	0.03	0.03	-	-
Tellurium	-	-	-	-
Tin	-	-	-	-
Tungsten	-	-	-	-
Vanadium	0.79	0.85	-	-
Zinc	-	-	-	-
Others	-	-	-	-

Mineral Intensity (kg/unit)			
Technology	EV LCO	PHEV LMO	EV LFP
Aluminum	23.64	-	50.85
Cadmium	-	-	-
Chromium	-	-	-
Cobalt	78.64	-	-

Copper	33.18	36.99	80.34
Gallium	-	-	-
Germanium	-	-	-
Graphite	-	64.10	76.28
Indium	-	-	-
Iron	75.00	-	47.39
Lead	-	-	-
Lithium	9.09	7.91	7.05
Manganese	-	104.91	-
Molybdenum	-	-	-
Nickel	5.45	-	-
Phosphorus Rock	-	-	-
PGM	-	-	-
REE	-	-	-
Silicon	-	-	-
Silver	-	-	-
Tellurium	-	-	-
Tin	-	-	-
Tungsten	-	-	-
Vanadium	-	-	-
Zinc	-	-	-
Others	-	-	-

Table 5. EV mineral intensity. Source: IEA.

To assess the demand for minerals in electric transportation, it is essential to project the number of electric vehicles that will be developed by technology in the coming years according to the different scenarios. As with previous projections, the figures for intermediate years have been calculated using linear regression between target years. The primary sources of information for these projections are the International Energy Agency, along with reports from McKinsey and other reputable automotive consulting firms.

Annual EV Sales							
Technology	2010	2011	2012	2013	2014	2015	2016
BEV cars	7,200	39,000	58,000	110,000	200,000	330,000	460,000
BEV bus	2,000	680	1,600	2,200	4,300	94,000	91,000

BEV trucks	24	300	450	910	380	17,000	15,000
BEV vans	1,600	3,700	11,000	11,000	11,000	27,000	23,000
Total BEV	10,824	43,680	71,050	124,110	215,680	468,000	589,000
PHEV cars	370	9,000	60,000	91,000	130,000	220,000	290,000
PHEV bus	-	330	1,000	3,500	12,000	27,000	15,000
PHEV trucks	-	-	-	-	-	-	-
PHEV vans	-	-	11	5	20	780	170
Total PHEV	370	9,330	61,011	94,505	142,020	247,780	305,170
Total EV	11,194	53,010	132,061	218,615	357,700	715,780	894,170

Annual EV Sales						
Technology	2017	2018	2019	2020	2021	2022
BEV cars	760,000	1,400,000	1,500,000	2,000,000	4,600,000	7,300,000
BEV bus	91,000	96,000	79,000	70,000	55,000	63,000
BEV trucks	67,000	54,000	36,000	34,000	40,000	58,000
BEV vans	86,000	80,000	59,000	84,000	150,000	300,000
Total BEV	1,004,000	1,630,000	1,674,000	2,188,000	4,845,000	7,721,000
PHEV cars	420,000	650,000	580,000	970,000	1,900,000	2,900,000
PHEV bus	530	2,600	2,700	3,700	1,900	2,400
PHEV trucks	14,000	3,600	2,400	420	1,000	1,500
PHEV vans	140	190	280	2,500	6,300	7,900
Total PHEV	434,670	656,390	585,380	976,620	1,909,200	2,911,800
Total EV	1,438,670	2,286,390	2,259,380	3,164,620	6,754,200	10,632,800

Table 6. Historical annual EV sales. Source: IEA & McKinsey.

Annual EV Sales STEPS projections			
Technology	2025	2030	2050
BEV cars	16,000,000	31,000,000	48,639,757
BEV bus	260,000	350,000	549,159
BEV trucks	210,000	420,000	658,990
BEV vans	950,000	2,100,000	3,294,951
Total BEV	17,420,000	33,870,000	53,142,857
PHEV cars	4,500,000	5,900,000	8,207,499
PHEV bus	15,000	27,000	37,560
PHEV trucks	86,000	240,000	333,864

PHEV vans	60,000	200,000	278,220
Total PHEV	4,661,000	6,367,000	8,857,143
Total EV	22,081,000	40,237,000	62,000,000

Table 7. Annual EV sales STEPS projections. Source: IEA & McKinsey.

Annual EV Sales APS projections			
Technology	2025	2030	2050
BEV cars	16,000,000	33,000,000	48,639,757
BEV bus	270,000	480,000	549,159
BEV trucks	240,000	750,000	658,990
BEV vans	1,000,000	2,800,000	3,294,951
Total BEV	17,510,000	37,030,000	53,142,857
PHEV cars	4,700,000	7,400,000	8,207,499
PHEV bus	16,000	38,000	37,560
PHEV trucks	84,000	190,000	333,864
PHEV vans	84,000	360,000	278,220
Total PHEV	4,884,000	7,988,000	8,857,143
Total EV	22,394,000	45,018,000	62,000,000

Table 8. Annual EV sales APS projections. Source: IEA & McKinsey.

The next step involves identifying the inputs necessary to correlate the minerals required for various industries with global socio-economic development. This study will be based on mineral extraction data sourced from historical databases such as the USGS and BGS, including information on mineral production, refining, reserves, and identified resources. To facilitate understanding, brief descriptions of these concepts will be provided, followed by tables presenting historical data for each mineral. It is important to note that there is no official record for all the minerals analyzed, as some are by-products of mines primarily extracting other minerals or originate from mines in regions with low levels of social development and data recording.

- Mineral production refers to the process of extracting valuable minerals from the earth. This includes the mining and initial processing of ores to separate the desired minerals from the surrounding material. The quantity of minerals produced is typically measured in terms of weight or volume and reflects the output from mining operations over a specified period.

- Mineral refining involves further processing of extracted minerals to purify and convert them into usable forms. This process includes chemical, thermal, and physical treatments to remove impurities and produce high-quality mineral products. Refining is essential for transforming raw minerals into forms suitable for industrial applications, such as metal production and manufacturing.
- Mineral reserves are the economically viable portions of identified mineral resources. These reserves are quantities of minerals that are confirmed through exploration and are extractable under current economic and technological conditions. Reserves are classified into proven and probable categories based on the level of confidence in their existence and economic feasibility.
- Identified mineral resources encompass all known quantities of minerals, regardless of their economic viability. These resources include both discovered deposits that are currently uneconomical to extract and those that may become viable with future technological advances or changes in market conditions. Identified resources provide a broader understanding of the potential mineral wealth within a region or globally.

Copper mineral data (tonnes)				
Year	Production	Refinery	Reserves	Identified Resource
1970	6,202,478	-	280,000,000	-
1971	6,278,422	-	305,600,000	-
1972	7,019,954	-	331,200,000	-
1973	7,477,898	-	356,800,000	-
1974	7,660,355	-	382,400,000	-
1975	7,241,592	-	408,000,000	-
1976	7,836,276	-	396,400,000	-
1977	7,940,945	9,212,449	384,800,000	-
1978	7,906,860	9,382,976	373,200,000	-
1979	7,912,257	9,583,577	361,600,000	-
1980	7,739,464	9,474,946	350,000,000	-
1981	8,162,994	9,630,352	348,000,000	-
1982	8,034,917	9,482,873	346,000,000	-
1983	8,113,058	9,740,885	344,000,000	-
1984	8,348,004	9,604,325	342,000,000	-

1985	8,409,241	9,632,609	340,000,000	-
1986	8,498,381	9,829,102	337,200,000	-
1987	8,786,976	10,149,801	334,400,000	-
1988	8,907,074	10,439,424	331,600,000	-
1989	9,334,657	10,822,020	328,800,000	-
1990	9,327,015	10,674,541	326,000,000	-
1991	9,196,933	10,571,625	322,800,000	-
1992	9,581,402	11,093,611	319,600,000	-
1993	9,667,947	11,254,189	316,400,000	-
1994	9,667,190	11,189,807	313,200,000	-
1995	10,238,121	11,890,968	310,000,000	-
1996	11,064,264	12,754,302	310,000,000	-
1997	11,472,831	13,641,895	320,000,000	-
1998	12,316,410	14,063,474	340,000,000	-
1999	12,797,343	14,481,483	340,000,000	-
2000	13,206,324	14,773,972	340,000,000	-
2001	13,652,544	15,582,521	340,000,000	-
2002	13,516,923	15,308,424	480,000,000	-
2003	13,637,943	15,267,914	470,000,000	-
2004	14,524,236	15,875,436	470,000,000	-
2005	14,958,389	16,662,614	470,000,000	-
2006	15,066,687	17,223,775	480,000,000	-
2007	15,502,548	17,772,248	490,000,000	-
2008	15,602,299	18,251,864	550,000,000	-
2009	15,803,948	18,319,080	540,000,000	-
2010	16,102,375	19,096,479	630,000,000	-
2011	15,989,615	19,502,614	690,000,000	-
2012	16,753,333	19,977,975	680,000,000	-
2013	18,295,037	21,050,105	690,000,000	-
2014	18,566,941	22,444,438	700,000,000	-
2015	19,290,301	23,053,718	720,000,000	2,000,000,000
2016	20,397,215	23,429,785	720,000,000	2,100,000,000
2017	20,026,902	23,681,583	790,000,000	2,100,000,000
2018	20,589,220	23,997,459	830,000,000	2,100,000,000
2019	20,569,688	24,703,135	870,000,000	2,100,000,000
2020	20,635,773	24,855,756	870,000,000	2,100,000,000

2021	21,200,000	24,846,235	875,800,000	2,100,000,000
2022	21,900,000	-	885,600,000	2,100,000,000

Table 9. Copper mineral data. Source: BGS & USGS.

To model the growth of mineral demand associated with socio-economic development, it is necessary to utilize inputs of socio-economic variables and their future projections. The primary variables employed in this analysis include GDP, population, level of urbanization, and year, as well as combinations of these factors. The following tables present the values used in the correlations for the base demand, with the detailed model to be developed in subsequent sections.

Socio-economic Variables				
Year	GDP (billion \$)	GDP growth	Population (m)	Urb Level
1970	18,093.04	3.97	3,690.31	36.60
1971	18,866.75	4.28	3,768.02	36.82
1972	19,926.32	5.62	3,843.70	37.04
1973	21,203.09	6.41	3,920.10	37.26
1974	21,583.77	1.80	3,995.97	37.48
1975	21,720.58	0.63	4,070.11	37.70
1976	22,872.46	5.30	4,143.19	38.02
1977	23,810.12	4.10	4,215.94	38.34
1978	24,795.15	4.14	4,289.91	38.66
1979	25,830.55	4.18	4,365.85	38.98
1980	26,315.44	1.88	4,442.44	39.30
1981	26,823.89	1.93	4,520.99	39.68
1982	26,929.50	0.39	4,602.76	40.06
1983	27,642.89	2.65	4,684.94	40.44
1984	28,935.05	4.67	4,766.72	40.82
1985	30,005.25	3.70	4,850.16	41.20
1986	31,038.29	3.44	4,936.10	41.56
1987	32,196.69	3.73	5,024.39	41.92
1988	33,690.06	4.64	5,113.49	42.28
1989	34,954.87	3.75	5,202.70	42.64
1990	35,956.65	2.87	5,293.52	43.00
1991	36,481.55	1.46	5,382.66	43.36

1992	37,236.63	2.07	5,470.28	43.72
1993	37,909.93	1.81	5,556.72	44.08
1994	39,163.00	3.31	5,642.13	44.44
1995	40,373.94	3.09	5,726.80	44.80
1996	41,824.66	3.59	5,811.62	45.18
1997	43,446.51	3.88	5,896.08	45.56
1998	44,671.35	2.82	5,979.73	45.94
1999	46,258.45	3.55	6,062.28	46.32
2000	48,347.00	4.51	6,144.32	46.70
2001	49,318.39	2.01	6,226.34	47.20
2002	50,455.09	2.30	6,308.09	47.70
2003	52,024.05	3.11	6,389.38	48.20
2004	54,350.17	4.47	6,470.82	48.70
2005	56,526.68	4.00	6,552.57	49.20
2006	59,025.40	4.42	6,634.94	49.70
2007	61,611.83	4.38	6,717.64	50.20
2008	62,886.69	2.07	6,801.41	50.70
2009	62,043.10	-1.34	6,885.49	51.20
2010	64,860.38	4.54	6,969.63	51.70
2011	67,007.46	3.31	7,053.53	52.14
2012	68,822.30	2.71	7,140.90	52.58
2013	70,754.75	2.81	7,229.18	53.02
2014	72,941.53	3.09	7,317.51	53.46
2015	75,186.36	3.08	7,404.91	53.90
2016	77,295.54	2.81	7,491.93	54.35
2017	79,912.95	3.39	7,578.16	54.81
2018	82,539.58	3.29	7,661.78	55.26
2019	84,678.53	2.59	7,742.68	55.72
2020	82,041.01	-3.11	7,820.98	56.17
2021	86,860.28	5.87	7,888.41	56.60
2022	89,379.23	2.90	7,941.66	57.04
2023	90,898.68	1.70	8,008.55	57.47
2024	93,352.94	2.70	8,082.07	57.90
2025	95,985.50	2.82	8,155.60	58.33
2026	98,692.29	2.82	8,228.38	58.74
2027	101,475.41	2.82	8,300.35	59.16

2028	104,337.02	2.82	8,371.60	59.57
2029	107,279.32	2.82	8,442.06	59.99
2030	109,725.29	2.28	8,511.72	60.40
2031	112,227.02	2.28	8,580.56	60.82
2032	114,785.80	2.28	8,648.51	61.24
2033	117,402.92	2.28	8,715.68	61.66
2034	120,079.70	2.28	8,781.92	62.08
2035	122,817.52	2.28	8,847.23	62.50
2036	125,617.76	2.28	8,911.56	62.90
2037	128,481.85	2.28	8,974.85	63.30
2038	131,411.23	2.28	9,037.20	63.70
2039	134,407.41	2.28	9,098.57	64.10
2040	137,471.90	2.28	9,158.75	64.50
2041	140,606.26	2.28	9,217.75	64.88
2042	143,812.08	2.28	9,275.59	65.26
2043	147,090.99	2.28	9,332.20	65.64
2044	150,444.67	2.28	9,387.47	66.02
2045	153,874.81	2.28	9,441.34	66.40
2046	157,383.15	2.28	9,493.74	66.80
2047	160,971.49	2.28	9,544.64	67.20
2048	164,641.64	2.28	9,593.96	67.60
2049	168,395.47	2.28	9,641.59	68.00
2050	172,234.88	2.28	9,687.44	68.40

Table 10. Socioeconomic variables for modelling 1970-2050. Source: Desk research.

Another significant aspect analyzed in this thesis is the energy requirements needed to extract the minerals demanded in the future, measured in millions of barrels of oil equivalent. This analysis serves as a reflection of the anticipated increase in energy consumption necessary to support the Energy Transition, as well as the associated CO₂ emissions from fossil fuel sources. The initial data, used as inputs, are derived from the article published by Emmanuel Aramendia, with 2015 as the base year. From this starting point, three different scenarios are projected: constant energy consumption, low consumption growth, and high consumption growth. The table below presents the energy consumption for 2015 and the coefficients that determine future consumption under these three scenarios.

Energy consumption referred to 2015	
Mineral	Energy (BOE/kt)
Aluminum	2,938.92
Cadmium	1,516.86
Chromium	511.94
Cobalt	3,602.54
Copper	5,024.60
Gallium	37,921.51
Germanium	37,921.51
Graphite	104.28
Indium	22,563.30
Iron	66.36
Lead	568.82
Lithium	1,185.05
Manganese	94.80
Molybdenum	18,297.13
Nickel	3,139.90
Phosphorus Rock	28.44
PGM	16,590,660.19
REE	3,792.15
Silicon	19.91
Silver	5,583,468.18
Tellurium	-
Tin	9,101.16
Tungsten	3,792.15
Vanadium	14,694.58
Zinc	602.00

Table 11. Mineral extraction energy required. Source: Emmanuel Aramendia "Global energy consumption of the mineral mining industry".

Energy consumption coefficients referred to 2015			
Year	Constant	Low growth	High Growth
2015	1.00	1.02	1.07
2016	1.00	1.03	1.09
2017	1.00	1.04	1.12
2018	1.00	1.05	1.15

2019	1.00	1.06	1.18
2020	1.00	1.07	1.21
2021	1.00	1.08	1.25
2022	1.00	1.09	1.28
2023	1.00	1.10	1.32
2024	1.00	1.11	1.36
2025	1.00	1.12	1.39
2026	1.00	1.13	1.43
2027	1.00	1.14	1.47
2028	1.00	1.16	1.51
2029	1.00	1.17	1.55
2030	1.00	1.18	1.58
2031	1.00	1.19	1.62
2032	1.00	1.20	1.66
2033	1.00	1.22	1.70
2034	1.00	1.23	1.74
2035	1.00	1.24	1.78
2036	1.00	1.25	1.82
2037	1.00	1.26	1.85
2038	1.00	1.28	1.89
2039	1.00	1.29	1.93
2040	1.00	1.30	1.97
2041	1.00	1.31	2.01
2042	1.00	1.32	2.05
2043	1.00	1.34	2.09
2044	1.00	1.35	2.13
2045	1.00	1.36	2.16
2046	1.00	1.37	2.20
2047	1.00	1.38	2.24
2048	1.00	1.40	2.28
2049	1.00	1.41	2.32
2050	1.00	1.42	2.36

Table 12. Mineral extraction coefficients future scenarios. Source: Emmanuel Aramendia "Global energy consumption of the mineral mining industry".

4.1.2. Demand Assumptions

This section outlines the primary assumptions made in the development of the model, all of which are based on comprehensive studies and projection reports. The data introduced in the previous section regarding installed capacity by technology at a global level do not account for sub-technologies. For instance, in the case of wind energy, no distinction is made between offshore and onshore wind farms, despite the former having a higher mineral intensity. Similarly, distinctions are not made for sub-technologies within solar energy, energy storage, or hydrogen production. To address this, each technology has been segmented into its various sub-technologies, with future projections developed based on historical data. Furthermore, a control panel has been introduced to this projection exercise, allowing for ongoing adjustments to enhance accuracy over time. Below is a detailed breakdown of the different sub-technologies for the target years:

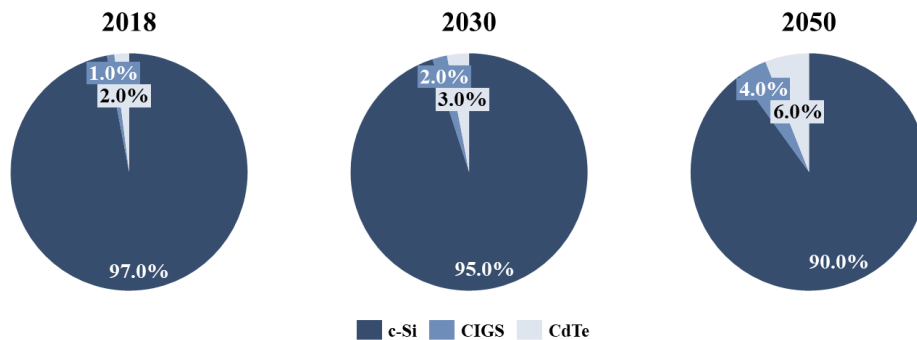


Figure 4.1. Solar energy subtechnologies. Source: Own development

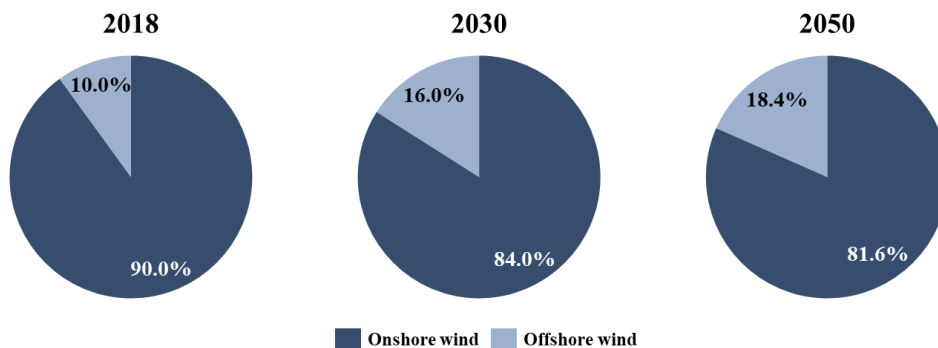


Figure 4.2. Wind energy subtechnologies. Source: Own development

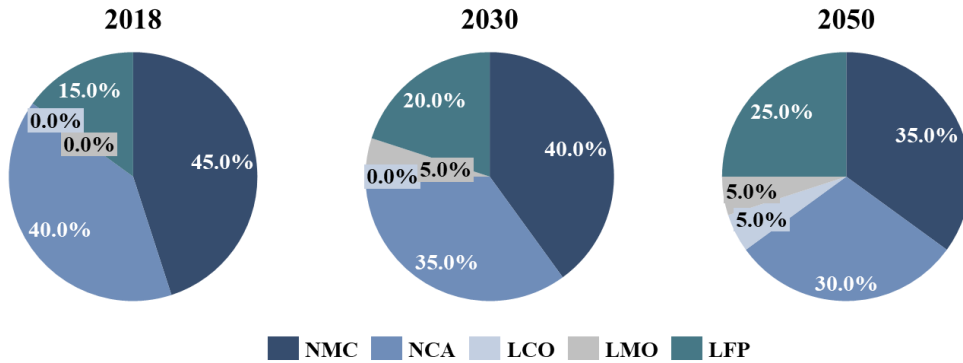


Figure 4.3. EV Batteries subtechnologies. Source: Own development

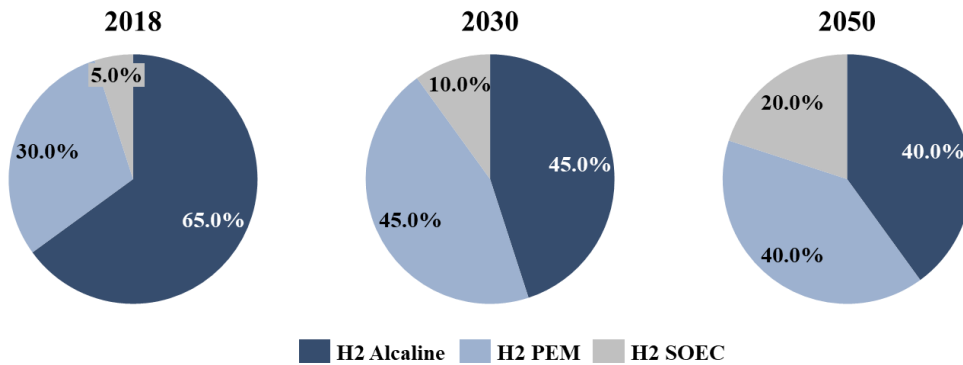


Figure 4.4. Hydrogen subtechnologies. Source: Own development

4.1.3. Demand Modeling

This section outlines the methodology used to model the prediction of mineral demand up to 2050 under various scenarios.

The initial step in modeling mineral demand, driven by the development of new renewable, nuclear, and electricity infrastructure capacity, involves calculating the annual increase in installed capacity for each technology. Additionally, the different technologies are segmented as described in the assumptions to determine the share of each sub-technology. This approach aims to estimate the MW installed for each sub-technology annually according to the different scenarios. As stated in the previous section, the model assumes that the mineral intensity per technology remains constant throughout the study period. Consequently, once the installed capacity is determined, it is multiplied by the

mineral intensity to calculate the annual mineral requirements needed to develop the respective capacities.

The next step in modeling mineral demand involves understanding the demand associated with other sectors and its correlation with socio-economic variables. First, the historical net base demand is calculated using a formula that considers ore refining and the previously calculated demands:

$$\text{Net Base Demand}_n = \text{Refined}_n - \text{RES}_n - \text{Nuclear}_n - \text{Transport}_n - \text{Hydrogen}_n$$

Once the net base demand is determined for each year in the historical series and for each mineral, linear regressions are simulated using an internal Excel tool. Different combinations of socio-economic variables and their respective natural logarithms are tested to identify the combination that best correlates with demand and presents the lowest error. The model utilizes 80% of the existing data as training data and 20% as test data to validate its accuracy. Additionally, the possibility of omitting the COVID-19 years has been considered, given the data uncertainties and the unrealistic slowdown in some industries' mineral demand during that period.

Regarding the combinations of variables, an initial simulation tested 15 different models for copper demand. The process was ultimately automated to identify the 10 models with the best results. Subsequently, the base demand for the remaining minerals was calculated using an iterative process, following these steps:

1. Preparation of refined mineral data
2. Calculation of historical net base demand
3. Adjustment of learning and test data batches based on known data
4. Simulation of 10 linear regression models and extraction of coefficients
5. Error calculation
6. Identification of the 3-4 models that best predict demand and analysis of their projections to 2050
7. Selection of the model that provides predictions consistent with historical data

The errors used to evaluate the models are described below:

- Root Mean Square Error is a widely used metric for assessing the accuracy of predictive models. It measures the square root of the average of the squared differences between predicted and observed values. Mathematically, it is expressed as:

$$RMSE = \sqrt{\frac{1}{n} \cdot \sum_{i=1}^n (y_i - \hat{y}_i)^2}$$

where y_i represents the observed values, \hat{y}_i denotes the predicted values, and n is the number of observations. RMSE provides a comprehensive measure of model accuracy by giving higher weight to larger errors due to the squaring of differences. This makes RMSE particularly useful when significant errors are undesirable and need to be penalized more. It is sensitive to outliers, which can disproportionately affect the score. RMSE is expressed in the same units as the observed values, facilitating interpretation. However, its sensitivity to larger errors can be a drawback in some contexts, especially if outliers are present.

- Mean Absolute Error is a straightforward and commonly used metric for evaluating the accuracy of predictive models. It measures the average magnitude of the errors between predicted and observed values, without considering their direction. Mathematically, MAE is defined as:

$$MAE = \frac{1}{n} \cdot \sum_{i=1}^n |y_i - \hat{y}_i|$$

MAE provides an easy-to-understand measure of model accuracy by calculating the mean of the absolute differences between predicted and actual values. Unlike RMSE, MAE treats all errors equally, giving a linear measure of average error. This makes MAE less sensitive to outliers and extreme values, providing a more balanced view of model performance in datasets with varying error magnitudes. MAE is also expressed in the same units as the observed values, simplifying its interpretation. It is particularly useful in scenarios where the magnitude of prediction errors needs to be minimized uniformly, without disproportionately penalizing larger errors.

- Mean Error, also known as bias, is a metric that measures the average difference between predicted and observed values. It is a simple measure that indicates

whether the model tends to overestimate or underestimate the actual values. Mathematically, ME is defined as:

$$ME = \frac{1}{n} \cdot \sum_{i=1}^n (y_i - \hat{y}_i)$$

ME provides insight into the systematic bias of a model by averaging the residuals (differences between actual and predicted values). A positive ME indicates that the model, on average, underestimates the observed values, while a negative ME suggests overestimation. Unlike previous errors presented, ME does not provide a measure of the magnitude of errors but rather focuses on the direction and overall tendency of the errors. This makes ME useful for diagnosing systematic errors in the model, helping to identify and correct consistent biases. However, ME can be misleading if positive and negative errors cancel each other out, resulting in a near-zero ME despite significant individual errors. Therefore, ME is often used in conjunction with other error metrics to provide a more comprehensive evaluation of model performance.

The results and coefficients from the base demand modeling for copper are presented in the following section. The results for the base demand modeling of other minerals are provided in Annex II.

	Model 1	Model 2	Model 3	Model 4	Model 5
Coeff\Variable	LN(GDPc), LN(Urb) & Year	GDPc, Urb & Year	GDPc & POP	GDPc, Pop & Urb	LN(GDPc), Pop & LN(Urb)
Intercept	-76.31069	-35.18681	7.90014	9.11770	6.78082
GDP	-	-	-	-	-
GDPc	-	0.00023	0.00016	0.00024	-
GDPg	-	-	-	-	-
POP	-	-	0.00006	0.00027	0.00039
POPg	-	-	-	-	-
Urb Level	-	-0.06430	-	-0.06583	-
Year	0.04531	0.02297	-	-	-
LN(GDP)	-	-	-	-	-
LN(GDPc)	2.02060	-	-	-	1.97263

LN(GDPg)	-	-	-	-	-
LN(POP)	-	-	-	-	-
LN(POPg)	-	-	-	-	-
LN(Urb Level)	-5.94007	-	-	-	-4.49640
LN(Year)	-	-	-	-	-
R2	0.97288	0.97287	0.97285	0.97380	0.97262

	Model 6	Model 7	Model 8	Model 9	Model 10
Coeff\Variable	GDPc, Pop & Year	LN(GDPc), Urb & Year	LN(GDPc), Pop & Urb	LN(GDPc), LN(Pop) & LN(Urb)	LN(GDPc), LN(Pop) & Urb
Intercept	218.54189	1.47091	-4.30115	-3.49183	0.16812
GDP	-	-	-	-	-
GDPc	0.00019	-	-	-	-
GDPg	-	-	-	-	-
POP	0.00132	-	-0.0000005	-	-
POPg	-	-	-	-	-
Urb Level	-	0.00754	-0.00100	-	0.02351
Year	-0.10929	-0.00294	-	-	-
LN(GDP)	-	-	-	-	-
LN(GDPc)	-	1.52007	1.55242	1.60976	1.36854
LN(GDPg)	-	-	-	-	-
LN(POP)	-	-	-	-0.36716	-0.45630
LN(POPg)	-	-	-	-	-
LN(Urb Level)	-	-	-	0.47439	-
LN(Year)	-	-	-	-	-
R2	0.97492	0.96841	0.96834	0.96916	0.96988

Table 13. Base demand forecast coefficients Copper. Source: Own development

Year	Model 1	Model 2	Model 3	Model 4	Model 5
2011	18,713.77	19,314.03	19,695.35	19,268.07	18,773.12
2012	19,178.36	19,838.05	20,253.49	19,807.66	19,247.65
2013	19,702.02	20,431.76	20,868.57	20,424.01	19,786.16
2014	20,366.89	21,196.04	21,612.28	21,215.53	20,462.68

2015	21,068.77	22,013.44	22,398.83	22,057.21	21,167.10
2016	21,660.74	22,724.62	23,130.22	22,789.07	21,766.77
2017	22,544.68	23,813.00	24,137.92	23,902.19	22,644.40
2018	23,450.96	24,951.96	25,184.41	25,050.25	23,517.75
2019	24,095.45	25,758.66	25,997.47	25,838.75	24,105.42
2020	22,082.63	23,070.86	24,277.13	23,045.84	22,073.52
2021	24,353.39	25,922.00	26,552.23	25,818.24	24,098.32

Year	Model 6	Model 7	Model 8	Model 9	Model 10	Real Demand
2011	19,590.85	19,285.03	19,190.91	19,422.59	19,633.30	18,990.73
2012	20,232.87	19,719.59	19,615.76	19,867.94	20,119.33	19,427.11
2013	20,967.91	20,194.30	20,080.84	20,355.38	20,645.53	20,481.26
2014	21,859.12	20,771.51	20,649.41	20,952.49	21,270.88	21,856.70
2015	22,781.17	21,369.88	21,238.82	21,573.54	21,922.18	22,404.02
2016	23,631.87	21,906.00	21,761.62	22,129.05	22,527.35	22,735.83
2017	24,789.29	22,657.04	22,501.62	22,915.85	23,338.70	22,877.75
2018	25,912.77	23,416.30	23,249.04	23,715.14	24,168.15	23,088.58
2019	26,664.59	23,970.85	23,788.02	24,298.61	24,818.01	23,792.40
2020	24,356.39	22,509.28	22,285.76	22,724.54	23,584.59	23,811.28
2021	26,347.42	24,238.78	24,017.30	24,581.42	25,360.31	23,221.72

Table 14. Base demand forecast results - Copper. Source: Own development

Year	Model 1	Model 2	Model 3	Model 4	Model 5
2011	276.96	-323.30	-704.62	-277.34	217.61
2012	248.75	-410.94	-826.38	-380.55	179.46
2013	779.24	49.50	-387.31	57.25	695.10
2014	1,489.82	660.66	244.42	641.17	1,394.03
2015	1,335.25	390.58	5.19	346.81	1,236.93
2016	1,075.09	11.21	-394.40	-53.24	969.06
2017	333.06	-935.25	-1,260.17	-1,024.45	233.35
2018	-362.38	-1,863.38	-2,095.83	-1,961.68	-429.17
2019	-303.05	-1,966.26	-2,205.08	-2,046.36	-313.02
2020	1,728.65	740.42	-465.85	765.44	1,737.76
2021	-1,131.67	-2,700.28	-3,330.51	-2,596.52	-876.60

Year	Model 6	Model 7	Model 8	Model 9	Model 10
2011	-600.12	-294.30	-200.18	-431.86	-642.57
2012	-805.76	-292.48	-188.65	-440.83	-692.22
2013	-486.65	286.96	400.42	125.88	-164.27
2014	-2.42	1,085.19	1,207.29	904.21	585.82
2015	-377.15	1,034.14	1,165.21	830.48	481.84
2016	-896.04	829.82	974.21	606.77	208.47
2017	-1,911.54	220.70	376.13	-38.11	-460.95
2018	-2,824.20	-327.73	-160.46	-626.56	-1,079.58
2019	-2,872.20	-178.45	4.37	-506.21	-1,025.62
2020	-545.12	1,302.00	1,525.51	1,086.73	226.69
2021	-3,125.69	-1,017.05	-795.58	-1,359.69	-2,138.59

Table 15. Base demand forecast errors - Copper. Source: Own development

Errors	Model 1	Model 2	Model 3	Model 4	Model 5
RSME	977.34	1,240.15	1,467.74	1,249.45	909.54
MAE	823.99	913.80	1,083.61	922.80	752.92
ME	497.25	-577.00	-1,038.23	-593.59	458.59

Errors	Model 6	Model 7	Model 8	Model 9	Model 10
RSME	1,709.28	745.15	804.97	735.60	883.83
MAE	1,313.35	624.44	636.18	632.49	700.60
ME	-1,313.35	240.80	391.66	13.71	-427.36

Table 16. Base demand forecast error summary - Copper. Source: Own development

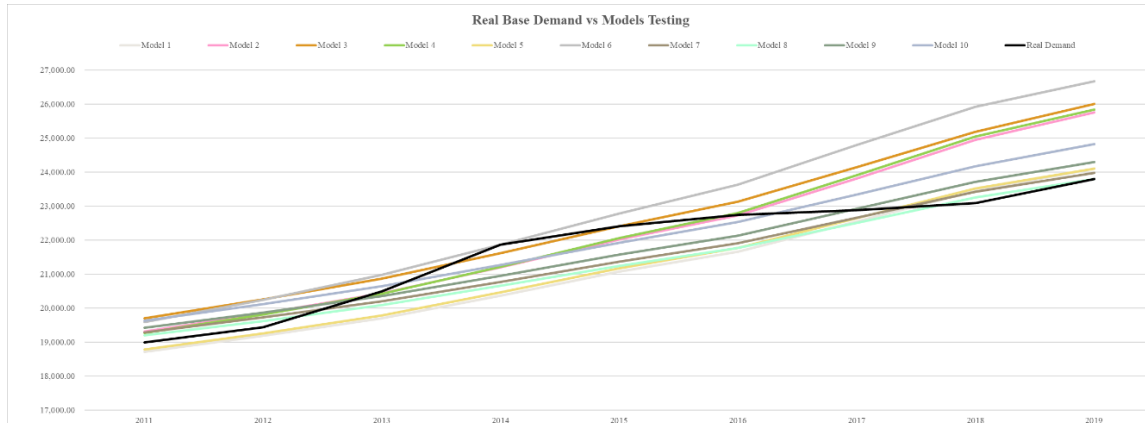


Table 17. Copper base demand vs models testing results. Source: Own development

Based on the results presented above, it has been determined that the regression model which best fits the potential future demand for copper is Model 7, incorporating the socio-economic variables LN(GDPc), urbanization level, and year.

The final step in the demand model involves calculating the total energy required for mineral extraction once the annual demand for each mineral is determined. This is achieved by multiplying the total annual demand by the energy needed for the extraction of each specific mineral. Additionally, for minerals where an approximate value of CO2 emissions during extraction is available, the associated increase in emissions due to the mining or processing of these minerals can be estimated. This comprehensive approach not only quantifies the energy requirements but also provides insights into the environmental impact, specifically the carbon footprint, associated with the projected increase in mineral demand.

4.2. Supply Forecast

This section does not focus on different development scenarios, as discussed in the section on mineral demand. Instead, it examines the capacity to increase mineral extraction in alignment with various trends. This analysis aims to evaluate the status of each mineral in terms of resource extraction and to determine if strategic shifts to alternative materials are necessary in the event of potential shortages.

4.2.1. Supply Inputs

In this section on mineral supply, the data previously presented in the demand section covering production, refining, reserves, and identified resources will serve as the foundation. Additionally, mineral recycling is becoming increasingly significant in the supply of minerals. Some minerals analyzed in this thesis exhibit a high degree of recyclability, while others currently lack the technological capacity for economically viable recycling, preventing the closure of the lifecycle once they reach the end of their useful life. The following data, extracted from a study by Emmanuel Aramendia, provide recycling information with a base year of 2015 and projections under three scenarios of future recycling growth. These scenarios consider the impetus of the Energy Transition and the high extraction costs of certain minerals, which are expected to drive the development of new technologies that will enable greater recovery of minerals post-use.

Recycle Rates	
Mineral	Recycle rates (%)
Aluminum	35.0%
Cadmium	15.0%
Chromium	19.0%
Cobalt	32.0%
Copper	28.5%
Gallium	37.5%
Germanium	42.5%
Graphite	3.5%
Indium	0.0%
Iron	40.0%
Lead	52.5%
Lithium	0.0%
Manganese	37.0%
Molybdenum	33.0%
Nickel	35.0%
Phosphorus Rock	0.0%
PGM	60.0%
REE	0.0%
Silicon	3.5%

Silver	26.0%
Tellurium	0.0%
Tin	22.0%
Tungsten	46.0%
Vanadium	0.0%
Zinc	22.5%

Table 18. Mineral recycling rates. Source: Emmanuel Aramendia "Global energy consumption of the mineral mining industry".

Recycle rates coefficients referred to 2015			
Year	Constant	Low growth	High Growth
2015	1.00	1.01	1.02
2016	1.00	1.02	1.04
2017	1.00	1.03	1.07
2018	1.00	1.04	1.09
2019	1.00	1.06	1.11
2020	1.00	1.07	1.13
2021	1.00	1.08	1.16
2022	1.00	1.09	1.18
2023	1.00	1.10	1.20
2024	1.00	1.11	1.22
2025	1.00	1.12	1.24
2026	1.00	1.13	1.27
2027	1.00	1.14	1.29
2028	1.00	1.16	1.31
2029	1.00	1.17	1.33
2030	1.00	1.18	1.36
2031	1.00	1.19	1.38
2032	1.00	1.20	1.40
2033	1.00	1.21	1.42
2034	1.00	1.22	1.44
2035	1.00	1.23	1.47
2036	1.00	1.24	1.49
2037	1.00	1.26	1.51
2038	1.00	1.27	1.53
2039	1.00	1.28	1.56

2040	1.00	1.29	1.58
2041	1.00	1.30	1.60
2042	1.00	1.31	1.62
2043	1.00	1.32	1.64
2044	1.00	1.33	1.67
2045	1.00	1.34	1.69
2046	1.00	1.36	1.71
2047	1.00	1.37	1.73
2048	1.00	1.38	1.76
2049	1.00	1.39	1.78
2050	1.00	1.01	1.02

Table 19. Mineral recycling rates future coefficients. Source: Emmanuel Aramendia "Global energy consumption of the mineral mining industry".

4.2.2. Supply Assumptions

The only assumption considered in this section is the useful life of each mineral, which refers to the duration during which the mineral remains in use in a specific application or product before it is no longer viable for that purpose. Although this period can vary significantly depending on the type of mineral and its application, a useful life of 30 years has been assumed for all minerals. This assumption will be reflected in the model as a lag in the recycling of minerals produced during those preceding years.

4.2.3. Supply Modelling

This section models ore supply capacities up to the year 2050 using various mathematical methods. These methods allow for a comparison of the projected increase in demand with historical ore extraction trends and reflect the impetus for new investment in mining operations. Understanding the potential growth of mining capacities is crucial, as it is well-known that as a mine becomes more exploited, extracting new ore becomes increasingly challenging. This results in higher energy requirements to obtain the same quantity of ore due to the reduction in ore grade. By modeling these supply capacities, it becomes possible to better anticipate the constraints and challenges associated with meeting future mineral demands and the corresponding need for technological advancements and increased energy efficiency in mining practices.

Based on the bibliography analyzed prior to the development of this thesis, several methods have been applied to project future mineral extraction. In consensus with this bibliography, this project will analyze two aspects of the future projection of mineral extraction using the production data presented in Annex I. The first aspect involves modeling the growth of mining extraction with a linear trend, considering the historical rate. This approach reflects the potential restrictions on minerals if the current rate of investment in new mines continues. The two mathematical models employed are described below:

- Holt Double Exponential Smoothing model is an extension of the simple exponential smoothing technique. It is designed to handle data with trends, offering a more sophisticated approach to forecasting compared to its predecessor. This model was introduced by Charles Holt in 1957 and improves upon the basic exponential smoothing by incorporating a mechanism to account for trends in the data. The HDES model operates using two equations: one for the level and one for the trend. The level equation smooths the data, while the trend equation smooths the trend. Mathematically, the model is represented as:

$$L_t = \alpha \cdot Y_t + (1 - \alpha) \cdot (L_{t-1} + T_{t+1})$$

$$T_t = \beta \cdot (L_t - L_{t-1}) + (1 - \beta) \cdot T_{t-1}$$

$$F_{t+m} = L_t + m \cdot T_t$$

Where L_t is the level component at time t, T_t is the trend component at time t, Y_t is the actual value at time t, α is the smoothing parameter for the level ($0 < \alpha < 1$), β is the smoothing parameter for the trend ($0 < \beta < 1$), and F_{t+m} is the forecast for m periods ahead.

The level equation updates the smoothed value of the series at each time period, accounting for both the actual data and the previous level and trend. The trend equation updates the trend component by smoothing the difference between the current and previous levels. The forecast equation uses the most recent estimates of the level and trend to project future values. Holt's method is particularly useful for forecasting time series data that exhibit a linear trend. It adapts to changes in the trend over time, providing more accurate forecasts compared to simple

exponential smoothing. The choice of smoothing parameters α and β is crucial and are determined through optimization techniques such as minimizing errors.

- ARIMA (AutoRegressive Integrated Moving Average) model is a comprehensive and versatile forecasting technique widely used for time series data. Developed by Box and Jenkins in the early 1970s, ARIMA is powerful due to its ability to model various types of time series patterns, including trends, seasonality, and autocorrelations. The ARIMA model combines three components: autoregression (AR), differencing (I), and moving average (MA). The general form of an ARIMA model is denoted as ARIMA(p,d,q), where p represents the number of autoregressive terms, d the number of differences needed to make the series stationary, and q the number of moving average terms. The mathematical model is expressed as:

$$Y_t = c + \phi_1 \cdot Y_{t-1} + \dots + \phi_p \cdot Y_{t-p} + \theta_1 \cdot \epsilon_{t-1} + \dots + \theta_q \cdot \epsilon_{t-q} + \epsilon_t$$

where Y_t is the actual value at time t, c a constant, ϕ_i the autoregressive coefficients, θ_j moving average coefficients, and ϵ_t white noise error term at time t.

The process begins with differencing the series d times to achieve stationarity, meaning the mean and variance of the series are constant over time. Once the series is stationary, the AR and MA components are identified. The AR component involves regressing the variable on its own lagged (past) values, while the MA component models the error terms as a linear combination of past error terms. Model identification involves determining the appropriate values for p , d , and q , often using tools like the autocorrelation function (ACF) and partial autocorrelation function (PACF) plots. Parameter estimation follows, typically using methods like maximum likelihood estimation or least squares. Finally, model diagnostics are performed to ensure the residuals (errors) resemble white noise.

Both models utilize a learning and testing methodology similar to that used in the demand model, with 80% of the data allocated for learning and 20% for testing. The Excel tool used for automating these models includes a macro that independently runs all minerals under study, optimizing for either the Mean absolute percentage error (MAPE)

or the Sum of squared errors (SSE). MAPE measures the accuracy of a forecast by calculating the average absolute percentage error between predicted and actual values. It is particularly useful for understanding the prediction accuracy in percentage terms, making it easy to interpret and compare across different datasets. On the other hand, SSE measures the total deviation of predicted values from actual values by summing the squared differences. This metric emphasizes larger errors due to the squaring of differences, making it sensitive to outliers and providing a comprehensive view of the model's accuracy.

For the copper production time series, an ARIMA model was implemented using RStudio to analyze the ACF and partial autocorrelation function PACF curves. This analysis facilitated the necessary transformations to ensure the data met the stationarity requirements for accurate forecasting. The results of these analyses and subsequent forecasts are presented below:

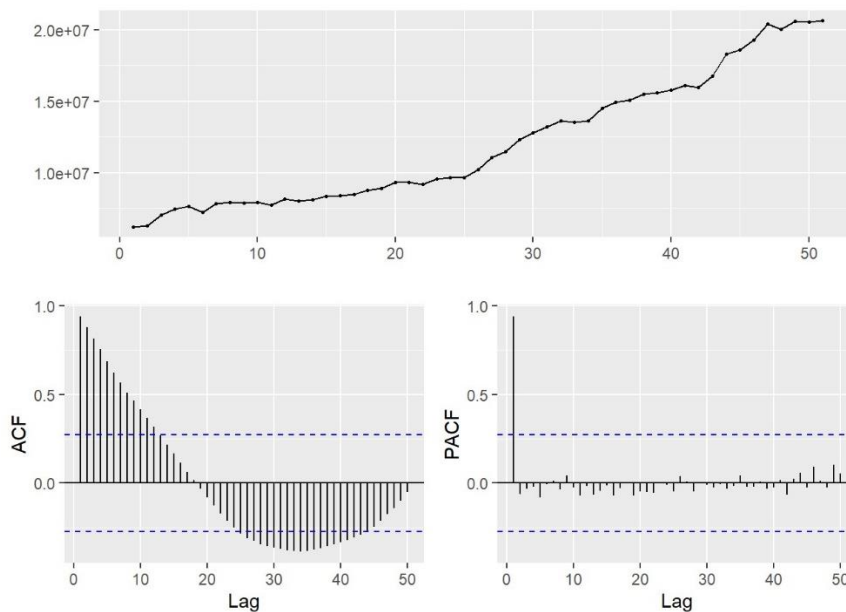


Figure 4.5. Copper production time series data since 1970 & ACF and PACF functions. Source: RStudio & Own development

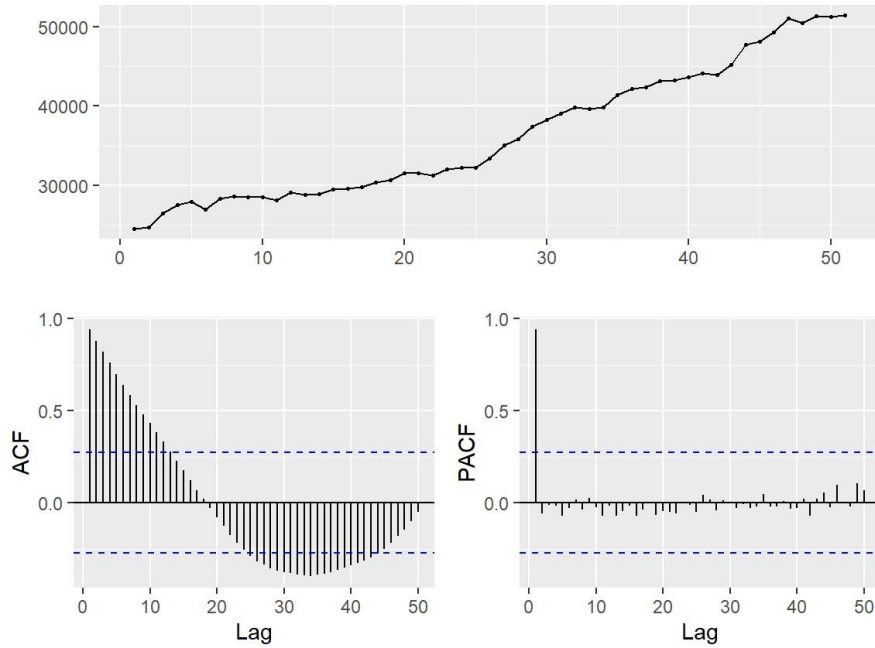


Figure 4.6. Time series CoxBox transformation plot. Source: RStudio & Own development

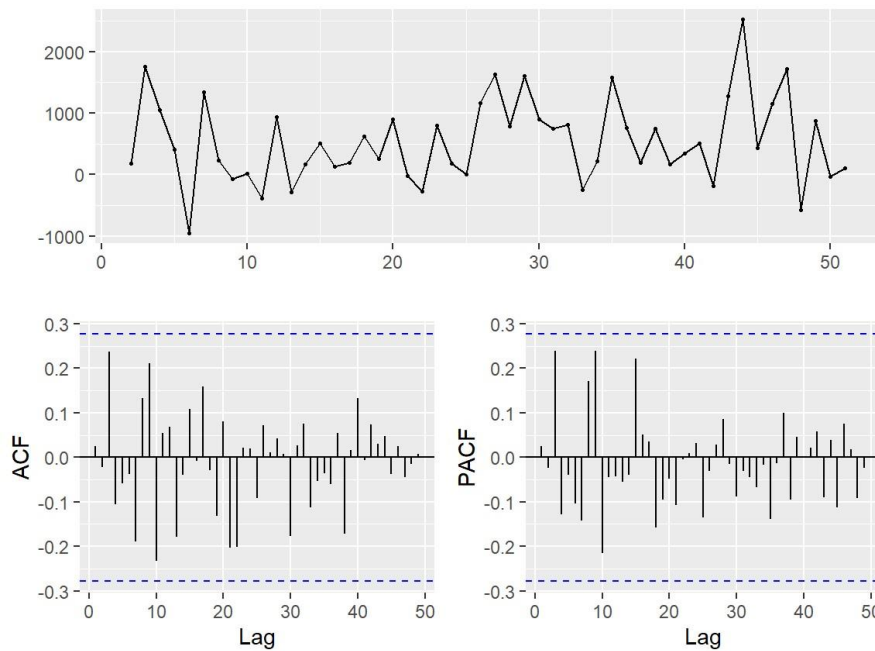


Figure 4.7. Time series 1st differentiation. Source: RStudio & Own development

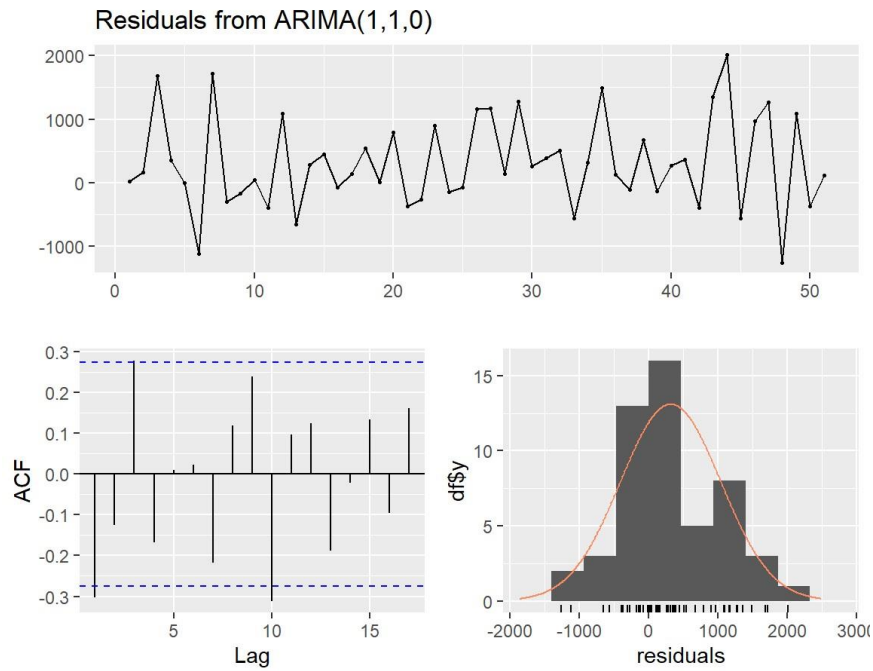


Figure 4.8. Time series ARIMA(1,1,0) model. Source: RStudio & Own development

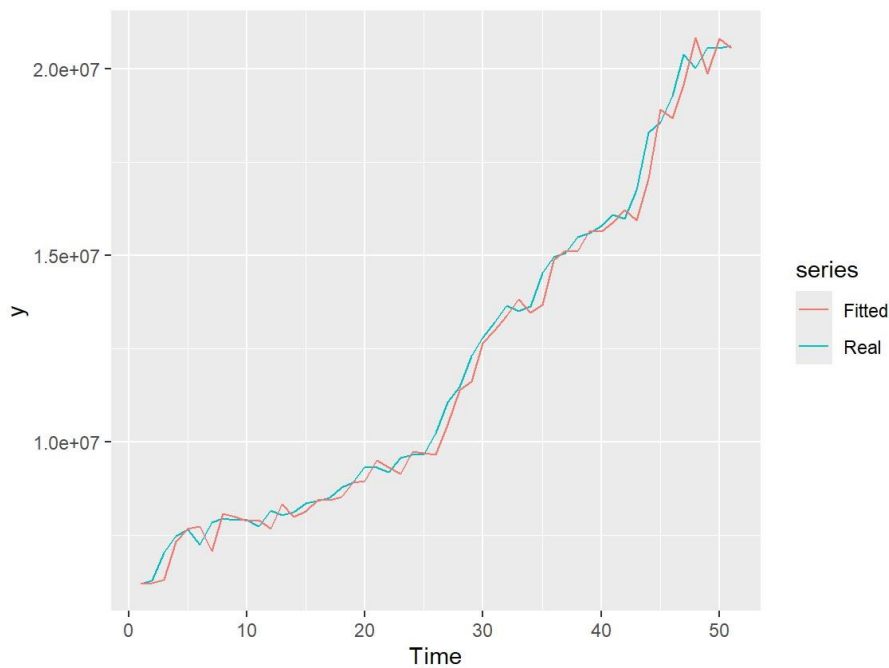


Figure 4.9. ARIMA forecast & real time series. Source: RStudio & Own development

The second aspect of the study examines the total extraction capacity considering the known reserves on the planet, focusing on reserves proven to be economically viable for extraction. This model has been replicated under various assumptions to understand the maximum extraction rate and the timeframe within which this rate would be achieved. This analysis employs Hubbert's Curves model, originally proposed by geophysicist M. King Hubbert in 1956, which is used to predict the production rates of a mineral resource over time. Although it was initially developed to forecast the production of fossil fuels, particularly petroleum, its principles have been adapted to various mineral extraction scenarios. The curve is a bell-shaped graph that illustrates the rise, peak, and eventual decline of resource extraction, assuming a finite resource with a fixed total amount available. The Hubbert Curve is grounded in the idea that production starts at a low rate, increases rapidly as extraction methods improve and demand grows, peaks when approximately half of the resource has been extracted, and then declines as the resource becomes increasingly scarce and harder to extract. This model is particularly useful in highlighting the finite nature of mineral resources and the inevitable peak and decline in production. Some of the key concepts that are included within the model are:

1. Exponential growth phase: Initially, the production rate increases exponentially due to technological advancements, increased investment, and rising demand. During this phase, new reserves are discovered, and production ramps up rapidly.
2. Peak production: The peak of the curve represents the point at which maximum production rate is achieved. At this point, approximately half of the total resource has been extracted. Hubbert's model assumes that this peak is inevitable due to the physical limitations of resource extraction.
3. Decline phase: Following the peak, production rates decline as the remaining resources become harder to extract. The decline is often steeper than the growth phase because of the depletion of easy-to-extract resources, increased extraction costs, and diminishing returns on investment.
4. Symmetry assumption: Hubbert's original model assumes that the production curve is symmetrical around the peak. This implies that the time taken to reach the peak is roughly equal to the time taken for production to decline to zero.

However, in practice, the symmetry may vary due to technological advancements, changes in economic conditions, new identified resources, and regulatory impacts.

The mathematical model for Hubbert's Curve involves various unknowns and parameters, which are crucial for representing the worst-case scenario in the event of resource depletion. The equations utilized in different models are outlined below, each incorporating distinct inputs and variables to provide a comprehensive analysis.

$$\text{Burn - off time} = \frac{\text{Known reserves}}{\text{Present production}}$$

$$URR = 4 \cdot \frac{P_{max}}{b}$$

$$m = \frac{URR}{1 + e^{-b \cdot (t - t_{max})}}$$

$$P(t) = \frac{2 \cdot P_{max}}{1 + \cosh(b \cdot (t - t_{max}))}$$

where URR represents the size of the whole resource identified, m the sum of all resource produce to time t, b an unknown curve shape constant, $P(t)$ production at time t, P_{max} maximum production, and t_{max} peak production year.

When applied to mineral extraction, Hubbert's Curve helps predict the lifecycle of mining operations for finite resources such as copper, gold, and rare earth elements. By analyzing historical production data and estimating total recoverable reserves, the model can forecast when production is likely to peak and how quickly it will decline thereafter. However, while Hubbert's Curve provides a valuable framework for understanding resource extraction dynamics, it has limitations. The assumption of symmetry and a fixed total resource can be overly simplistic. Technological advancements, economic fluctuations, and changes in market demand can all influence the actual production curve.

The next section will present all mineral supply results under both studied trends, along with the final results of the demand projections.

5. Results

5.1. Demand Results

The initial section of the results presents the mineral demand projections segmented by subcategory for the primary minerals analyzed. This is followed by a critical analysis of the implications for both the Energy Transition and the mining sector.

First, the section provides graphs illustrating the projected mineral demand until 2050 under the STEPS, APS, and NZE for copper. Additionally, a summary table is included, detailing the total demand projections for the other minerals analyzed.

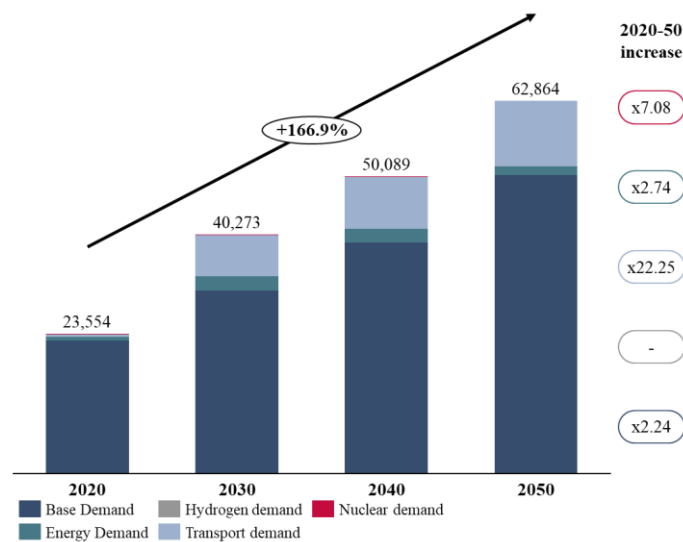


Figure 5.1. Annual copper demand (in kt) – STEPS scenario. Source: Own development

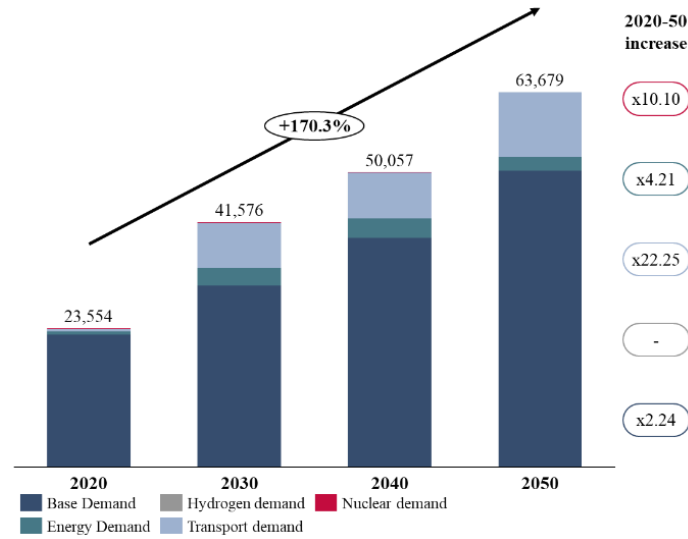


Figure 5.2. Annual copper demand (in kt) – APS scenario. Source: Own development

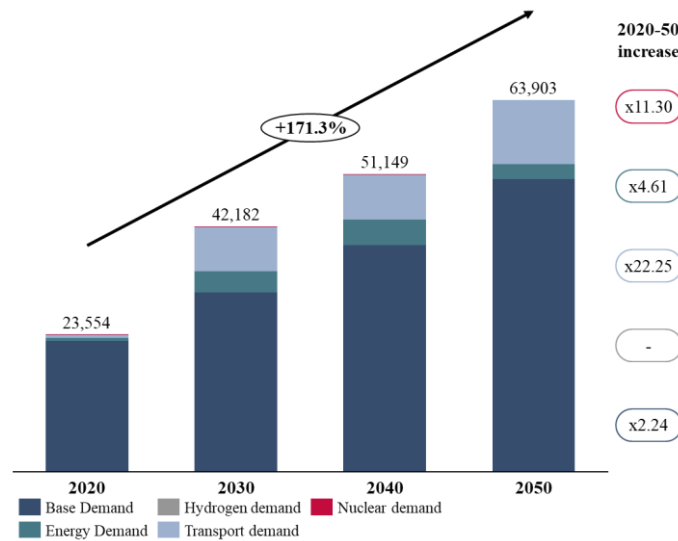


Figure 5.3. Annual copper demand (in kt) – NZE scenario. Source: Own development

The graphs above illustrate the projected annual copper demand, highlighting the increased mining capacity needed to support the Energy Transition. The various scenarios emphasize the rising importance of minerals associated with renewable generation technologies. Notably, the most significant surge in copper demand is expected to stem from the expansion of the electric vehicle fleet, with demand projected to multiply by a factor of 22.5.

Total demand (kt)				
Mineral	2021	2030	2040	2050
Aluminum	60,950.23	94,495.86	130,211.18	183,513.69
Cadmium	24.03	30.15	34.91	39.86
Cobalt	216.17	869.21	1,280.80	2,019.22
Copper	25,862.05	40,273.50	50,088.59	62,864.15
Iron	1,564,380.18	1,947,690.76	2,573,496.92	3,159,257.67
Lead	12,557.27	18,810.25	29,105.55	52,440.61
Lithium	161.65	721.78	920.67	1,124.82
Nickle	2,690.32	6,324.08	8,230.57	11,025.89
REE	79.48	179.49	208.49	242.00
Zinc	13,959.71	22,630.38	28,455.31	44,192.20

Table 20. Total annual mineral demand forecast – STEPS. Source: Own development

Total demand increase (absolute x times 2021)				
Mineral	2021	2030	2040	2050
Aluminum	1.0	1.6	2.1	3.0
Cadmium	1.0	1.3	1.5	1.7
Cobalt	1.0	4.0	5.9	9.3
Copper	1.0	1.6	1.9	2.4
Iron	1.0	1.2	1.6	2.0
Lead	1.0	1.5	2.3	4.2
Lithium	1.0	4.5	5.7	7.0
Nickle	1.0	2.4	3.1	4.1
REE	1.0	2.3	2.6	3.0
Zinc	1.0	1.6	2.0	3.2

Table 21. Annual mineral demand forecast increase – STEPS. Source: Own development

The results presented in the table above for the STEPS scenario reveal several important conclusions about the development of mineral demand in the coming years. The analysis distinguishes different groups of minerals based on their projected demand growth. Firstly, minerals that play a crucial role in electrical technologies are expected to see significant increases in demand. Aluminum demand is projected to nearly triple, from 60,950.23 kt in 2021 to 183,513.69 kt in 2050, reflecting strong growth in sectors such as transportation, packaging, and construction. Cobalt demand is forecasted to increase

dramatically from 216.17 kt in 2021 to 2,019.22 kt in 2050, indicating a significant expansion in battery production, especially for electric vehicles. Copper demand is expected to more than double, growing from 25,862.05 kt in 2021 to 62,864.15 kt in 2050, underscoring the growing need for copper in electrical infrastructures, renewable energy installations, and electric vehicles. Secondly, there are minerals whose demand will grow more moderately, and which are intensively used in other industries. Iron demand is projected to grow steadily from 1,564,380.18 kt in 2021 to 3,159,257.67 kt in 2050, reflecting continued industrial growth. Lead demand is also expected to grow substantially, from 12,557.27 kt in 2021 to 52,440.61 kt in 2050, driven by its use in batteries and other industrial applications. The next group includes emerging minerals for which demand will grow exponentially, posing a high risk of supply not keeping pace with demand. Lithium demand is expected to soar from 161.65 kt in 2021 to 1,124.82 kt in 2050, highlighting the crucial role of lithium in battery technologies for electric vehicles and renewable energy storage. Demand for nickel is projected to rise from 2,690.32 kt in 2021 to 11,025.89 kt in 2050, reflecting its importance in battery production and stainless-steel manufacturing. Demand for rare earth elements will grow significantly, from 79.48 kt in 2021 to 242.00 kt in 2050, underscoring their essential role in advanced technologies, including electronics and renewable energy systems. Finally, cadmium demand will grow more modestly, which may indicate a lower risk of depletion in the future. Overall, the projected increases in demand for minerals highlight the need for significant investments in mining infrastructure and technology to ensure a sustainable supply. The growth in demand, especially for minerals such as lithium, cobalt, and nickel, underscores the importance of developing efficient recycling processes and sustainable mining practices to mitigate environmental impacts. Furthermore, the significant increase in demand for critical minerals underlines the necessity for geopolitical strategies to ensure stable supply chains and manage resource dependence.

The next step in the demand analysis is to determine the total energy required for the extraction of these minerals, highlighting the future energy needs associated with the development of new renewable technologies. For the STEPS scenario, the energy demand is presented under for the copper forecast the three scenarios discussed in the previous chapter concerning the energy intensity of extraction. This analysis focuses solely on the

energy required for extraction, excluding the subsequent treatment processes necessary for some minerals.

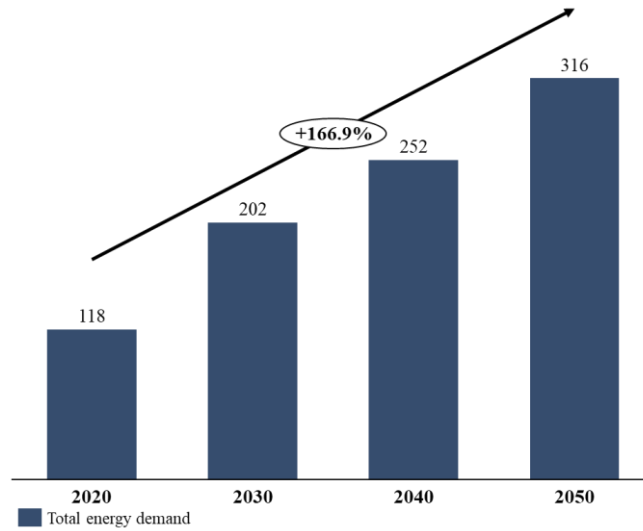


Figure 5.4. Copper extraction energy demand forecast under STEPS scenario (in mBOE) – Constant energy scenario. Source: Own development

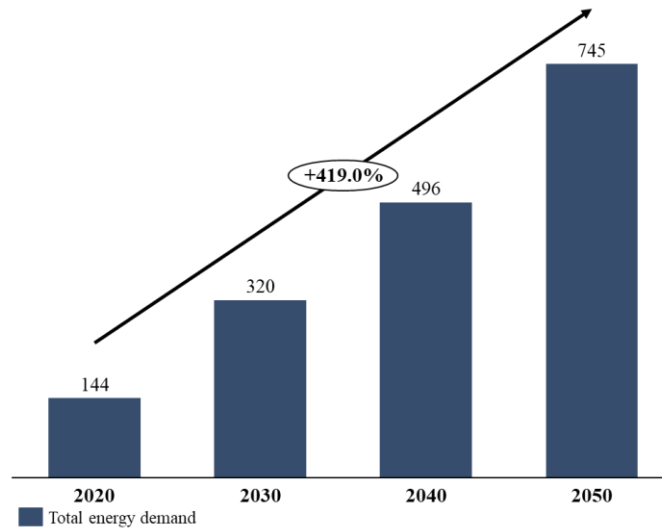


Figure 5.5. Copper extraction energy demand forecast under STEPS scenario (in mBOE) – High growth energy scenario. Source: Own development

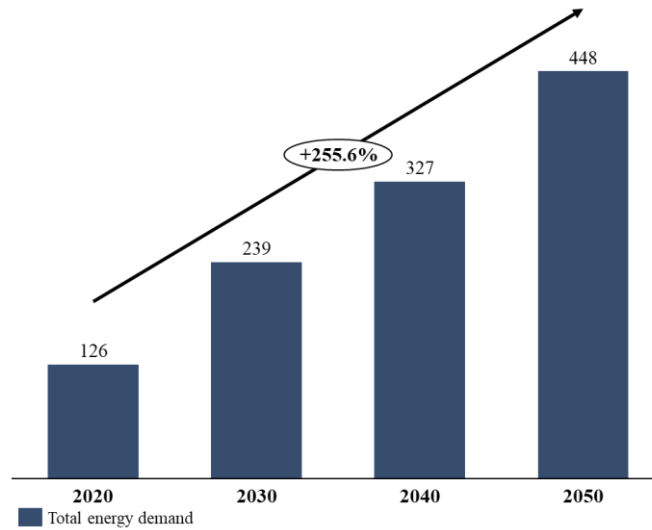


Figure 5.6. Copper extraction energy demand forecast under STEPS scenario (in mBOE) – Low growth energy scenario. Source: Own development

The above graphs underscore the critical role of mining in the energy landscape, emphasizing the substantial energy required not only to increase future ore extraction but also to maintain current copper production capacity. In the worst-case scenario, there is a projected more than fivefold increase in the energy currently used for extraction, contrasted with an anticipated nearly 2.5-fold increase in copper demand by 2050. This disparity reflects a situation where the energy required for extraction will escalate at twice the rate of the growth in mineral demand. This projection highlights the significant challenges that lie ahead in terms of energy consumption for mineral extraction, underscoring the need for advancements in extraction technologies, efficiency improvements, and sustainable practices to manage the increasing energy demands effectively. Below is a summary table for all the minerals analyzed, detailing the energy required for extraction under the worst-case scenario and the STEPS framework.

Energy extraction demand (mBOE)				
Mineral	2021	2030	2040	2050
Aluminum	223.24	439.27	753.61	1271.75
Cadmium	0.04	0.06	0.09	0.13
Cobalt	0.97	4.95	9.07	17.13
Copper	158.61	300.77	472.92	727.09
Iron	125.42	198.67	329.83	487.75
Lead	8.91	16.95	32.63	70.36
Lithium	0.24	1.31	2.06	3.05
Nickle	10.44	31.08	50.53	81.31
REE	0.34	0.97	1.47	2.10
Zinc	10.24	20.82	33.11	62.26

Table 22. Energy demand forecast under STEPS scenario (in mBOE) – High growth energy scenario.

Source: Own development

Energy extraction increase (absolute x times 2020)				
Mineral	2021	2030	2040	2050
Aluminum	1.00	1.97	3.38	5.70
Cadmium	1.00	1.44	2.03	2.90
Cobalt	1.00	5.09	9.34	17.65
Copper	1.00	1.90	2.98	4.58
Iron	1.00	1.58	2.63	3.89
Lead	1.00	1.90	3.66	7.90
Lithium	1.00	5.50	8.67	12.85
Nickle	1.00	2.98	4.84	7.79
REE	1.00	2.83	4.28	6.09
Zinc	1.00	2.03	3.23	6.08

Table 23. Energy demand forecast increase under STEPS scenario (in mBOE) – High growth energy scenario. Source: Own development

The summary tables for energy extraction demand under the STEPS scenario reveal several key insights, particularly highlighting the substantial increase in energy requirements compared to the growth in mineral demand. Notably, the energy demand for cobalt and lithium extraction is projected to rise dramatically. Cobalt's energy extraction demand is anticipated to escalate from 0.97 mBOE in 2021 to 17.13 mBOE in 2050, representing an increase of nearly 18 times. Similarly, lithium's energy extraction

demand is forecasted to surge from 0.24 mBOE in 2021 to 3.05 mBOE in 2050, a remarkable 13-fold increase. This discrepancy underscores the urgent need for advancements in energy efficiency and extraction technologies to manage the escalating energy demands associated with the increasing need for cobalt and lithium. Both of these minerals are essential for battery production and the broader Energy Transition. These findings highlight the critical importance of investing in sustainable mining practices and energy-efficient technologies to ensure the viability of future mineral supplies. They also stress the need for strategic planning and policy measures to address the energy challenges posed by the anticipated surge in mineral extraction activities essential for supporting the global Energy Transition.

Finally, it is important to note that the rising demand for minerals and the energy required for the exploration and exploitation of new mines will significantly increase CO₂ and other greenhouse gas emissions. This observation underscores the need to consider the broader climatic consequences associated with the drive towards greater penetration of renewable energy and electric vehicles in the energy and transport sectors. While these technologies are pivotal for reducing reliance on fossil fuels, it is crucial to evaluate the environmental trade-offs and potential hidden costs. The promotion of new technologies must, therefore, be balanced with a comprehensive understanding of their overall impact on climate change.

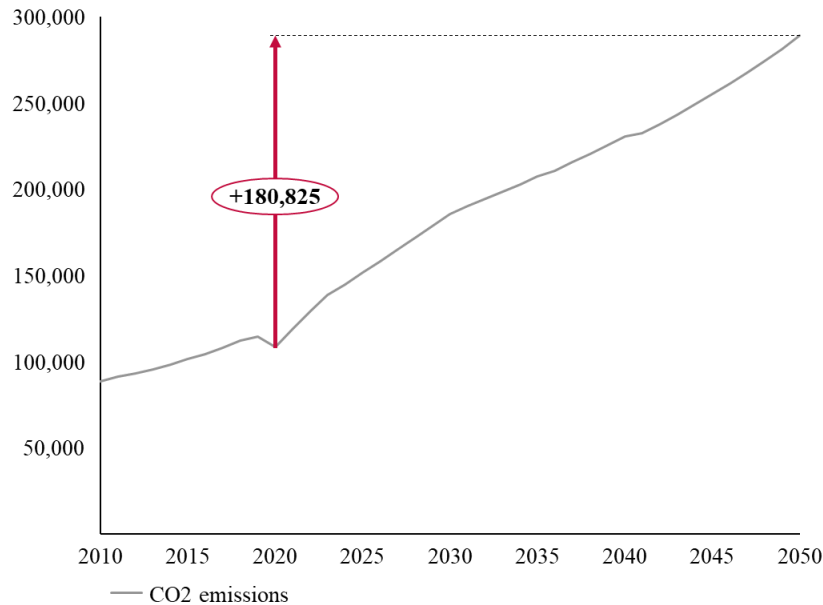


Figure 5.7. Annual CO2 emissions (in t) from copper mining – STEPS scenario. Source: Own development

The graph above indicates that copper mining in 2050 could result in the emission of approximately 300,000 tonnes of CO2 under a conservative scenario, assuming no advancements in cleaner extraction technologies. This projection should serve as a critical reminder of the environmental impact associated with current mining practices. It underscores the urgent need for investment in and development of more sustainable extraction methods. Additionally, it highlights the importance of integrating environmental considerations into the planning and implementation of mining activities to mitigate the adverse effects on climate change, and hidden carbon footprint of Energy Transition.

5.2. Supply Results

Given the projected demand for minerals driven by the Energy Transition and the development of other industries not directly related to energy policies, it is crucial to analyze the evolution of mineral production under various trends. This analysis will help understand potential future limitations and assess whether it will be possible to supply minerals to all industries. In this section, it will be present the results of projections using both a linear trend and an exponential growth approximation based on Hubbert curves.

This dual approach will provide a comprehensive view of the potential scenarios, highlighting the constraints and opportunities in meeting the increasing demand for minerals across different sectors.

First, the analysis of future production capacity is presented under a linear growth scenario, using the last years of production as a baseline. While projections are generated for the entire list of minerals, focusing on presenting graphs for the two most critical minerals: copper and cobalt. Additionally, a table summarizing the coefficients obtained for all minerals, derived from the optimization macro simulation of both relative and absolute errors, is included. This comprehensive analysis provides insights into the projected growth patterns and potential production capacities, enabling a better understanding of how future demands may be met.

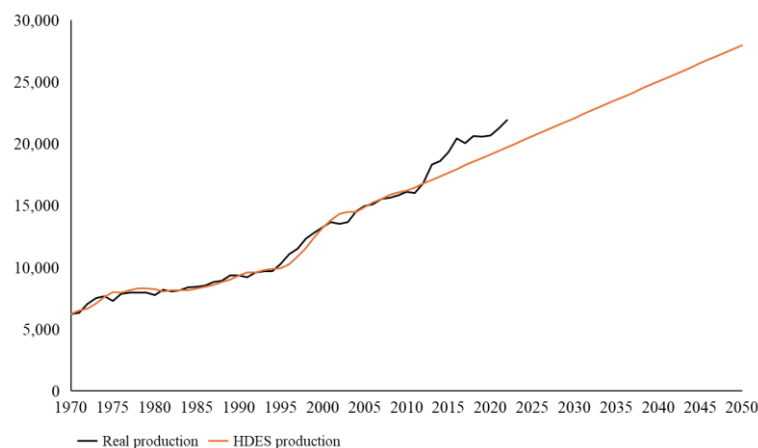


Figure 5.8. Copper production HDES forecast (in kt). Source: Own development

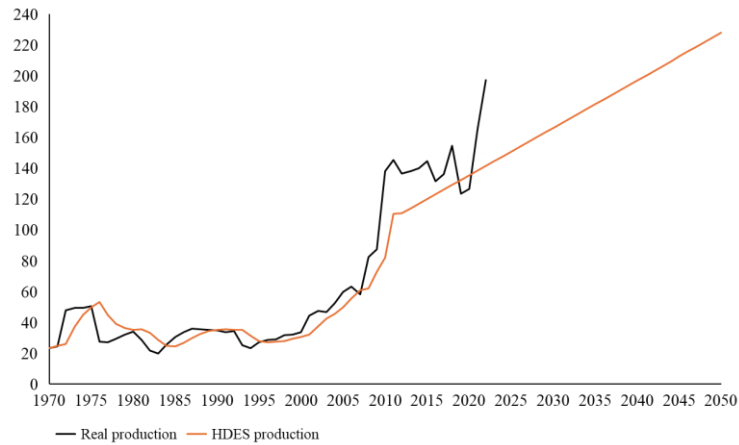


Figure 5.9. Cobalt production HDES forecast (in kt). Source: Own development

Mining production forecast HDES model				
Mineral	Alpha	Beta	SSE Error Test	MAPE Error test
Aluminum	0.40	0.40	686,337,998.36	15.8%
Cadmium	0.40	0.10	32.81	6.1%
Chromium	0.40	0.10	99,591,643.96	7.9%
Cobalt	0.40	0.10	4,584.21	16.4%
Copper	0.40	0.40	24,974,684.72	7.8%
Gallium	0.40	0.40	0.68	336.9%
Germanium	0.40	0.17	0.00	10.8%
Graphite	0.40	0.10	7,285,775.85	42.4%
Indium	0.40	0.40	0.06	7.8%
Iron	0.40	0.40	13,914,259,555,241	58.2%
Lead	0.40	0.40	20,192,088.33	40.6%
Lithium	0.40	0.40	399,798.38	39.9%
Manganese	0.40	0.40	2,239,631,760.69	38.2%
Molybdenum	0.40	0.16	7,285.56	9.4%
Nickel	0.40	0.25	4,320,298.73	30.5%
Phosphorus Rock	0.40	0.10	28,690,548,964.89	26.4%
PGM	0.40	0.10	32,701.42	10.1%
REE	0.40	0.40	118,155.11	-10379.8%
Silicon	0.10	0.10	-	0.0%
Silver	0.40	0.40	474,774,795.19	628599.0%
Tellurium	0.40	0.10	0.12	9.7%

Tin	0.40	0.22	2,788.13	-213.2%
Tungsten	0.40	0.40	89.30	120.5%
Vanadium	0.40	0.10	715.86	689.2%
Zinc	0.40	0.40	54,290,770.76	214347.0%

Table 24. Mineral production HDES methodology. Source: Own development

Mining production HDES model (kt)			
Mineral	2010	2020	2030
Aluminum	41,517.86	56,116.14	70,739.93
Cadmium	20.59	25.03	28.38
Chromium	23,394.54	34,305.38	43,436.31
Cobalt	82.03	135.21	166.01
Copper	16,202.10	19,110.40	22,058.59
Gallium	0.04	0.11	0.19
Germanium	0.12	0.10	0.08
Graphite	2,384.00	1,758.91	1,235.94
Indium	0.83	0.76	0.76
Iron	2,533,097.77	1,574,497.42	574,965.06
Lead	4,053.79	2,891.85	1,607.42
Lithium	123.52	739.76	1,350.63
Manganese	40,577.35	35,279.88	28,128.31
Molybdenum	228.75	282.67	330.07
Nickel	1,547.51	2,066.92	2,563.28
Phosphorus Rock	161,189.52	204,888.30	241,015.38
PGM	512.80	497.90	495.67
REE	141.13	401.48	669.87
Silicon	-	-	-
Silver	22,457.47	18,103.51	13,376.06
Tellurium	0.14	0.45	0.77
Tin	338.44	297.69	261.11
Tungsten	70.34	91.06	114.54
Vanadium	63.67	87.46	109.54
Zinc	12,358.16	8,955.74	5,501.07

Table 25. Mineral production HDES results. Source: Own development

The graphs and tables above illustrate the projected supply of various minerals under a linear trend scenario. It is noteworthy that some minerals exhibit a slower rate of mine production in the future, attributed to a downward trend in the historical data used for model training. This trend does not provide a realistic reflection of future production capacities, as evidenced by the high estimation errors in the test data. These significant errors indicate that a linear trend analysis may not be the most appropriate method for projecting mining extraction. Holt's model employs two parameters, alpha and beta, which are crucial for its performance. In the analysis, alpha and beta were set between 0.4 and 0.1. An alpha value of 0.4 means that 40% of the weight is given to the most recent observation when calculating the level component, while the remaining 60% is attributed to the historical data. This value indicates a moderate smoothing effect, balancing between responsiveness to recent changes and stability provided by past observations. A beta value of 0.1 indicates that only 10% of the weight is given to the most recent change in the trend component, while 90% relies on historical trends. This results in a smoother trend line that is less reactive to recent fluctuations, providing a more stable long-term trend projection. The chosen values of alpha and beta provide a balanced approach to smoothing, ensuring that the model does not overreact to recent short-term variations while still capturing long-term trends accurately. Despite this, the high errors observed in the test data suggest that the current linear trend assumptions may not be entirely suitable for all minerals.

The results of the ARIMA model are presented below, followed by a comparative analysis with the results obtained from the HDES model.

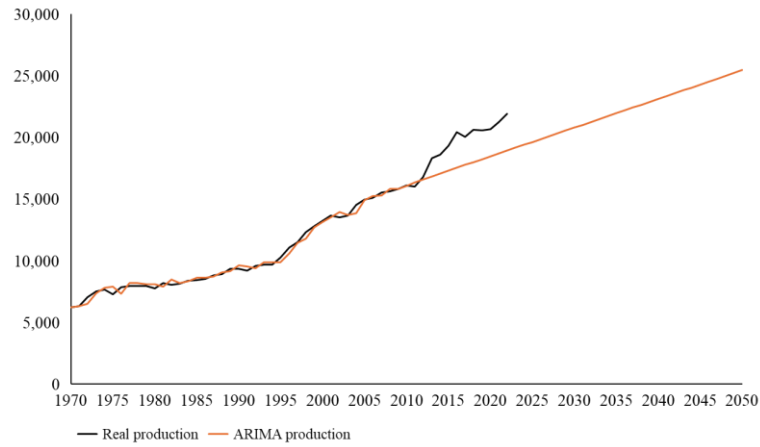


Figure 5.10. Copper production ARIMA forecast (in kt). Source: Own development

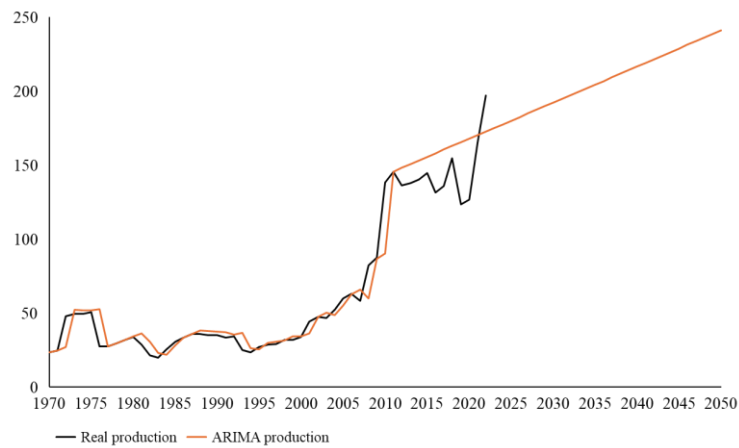


Figure 5.11. Cobalt production ARIMA forecast (in kt). Source: Own development

Mining production forecast ARIMA model				
Mineral	C	AR(1)	SSE Error Test	MAPE Error test
Aluminum	502.95	0.22	1,521,078,872	24.7%
Cadmium	0.06	-0.50	75	10.0%
Chromium	514.42	-0.09	133,970,365	9.2%
Cobalt	2.20	0.10	5,417	11.9%
Copper	178.45	0.23	39,251,593	10.1%
Gallium	-	0.38	1	835.2%
Germanium	-	1.00	0	42.0%
Graphite	41.73	0.20	15,837,745	50.9%

Indium	0.61	-0.95	36	64.2%
Iron	1.00	0.82	3,469,086,057,000	12.2%
Lead	13.98	-0.02	3,065,244	10.1%
Lithium	40.74	-0.57	76,688	26.0%
Manganese	1.00	0.19	397,308,384	12.4%
Molybdenum	4.22	-0.01	4,492	7.0%
Nickel	31.45	0.06	4,648,244	32.9%
Phosphorus Rock	1.00	0.35	25,465,806,932	24.2%
PGM	8.58	0.19	103,530	16.7%
REE	23.07	-0.53	20,168	20.5%
Silicon	1.00	1.00	7,942	100.0%
Silver	316.59	0.27	28,710,788	5.4%
Tellurium	0.01	0.01	1	126.4%
Tin	2.06	0.01	10,224	7.7%
Tungsten	1.48	-0.01	1,079	14.0%
Vanadium	1.23	-0.22	1,923	17.6%
Zinc	170.49	0.12	21,821,617	8.2%

Table 26. Mineral production ARIMA methodology. Source: Own development

Mining production ARIMA model (kt)			
Mineral	2010	2020	2030
Aluminum	37,003.58	48,902.37	55,320.81
Cadmium	21.32	22.87	23.26
Chromium	20,922.92	31,973.24	36,700.26
Cobalt	89.92	167.59	192.01
Copper	16,029.30	18,447.70	20,773.05
Gallium	0.04	0.04	0.04
Germanium	0.11	0.27	0.42
Graphite	2,233.41	2,613.81	3,135.59
Indium	1.23	3.81	6.96
Iron	2,321,142.99	4,036,451.80	4,235,460.21
Lead	3,901.54	4,489.00	4,626.31
Lithium	156.17	390.58	649.38
Manganese	34,048.02	47,619.22	47,631.51
Molybdenum	224.88	286.68	328.49
Nickel	1,371.80	1,952.04	2,285.60

Phosphorus Rock	156,116.44	192,017.50	192,033.30
PGM	468.03	589.13	695.12
REE	152.55	280.35	430.81
Silicon	1.00	55.00	210.00
Silver	22,878.11	27,944.13	32,265.39
Tellurium	0.16	0.21	0.28
Tin	316.61	349.07	369.95
Tungsten	64.81	78.10	92.77
Vanadium	58.08	76.23	86.35
Zinc	11,771.18	14,505.77	16,436.20

Table 27. Mineral production ARIMA results. Source: Own development

The results from the ARIMA model exhibit lower errors for most of the minerals under study compared to the HDES model. This indicates a better fit and higher reliability of the ARIMA model for short-term projections. However, despite these improvements, the projections still fall short of providing realistic conclusions for a linear mineral production growth scenario. This limitation suggests that even with enhanced modeling techniques, capturing the complexities of mineral production dynamics remains challenging. To address this, the ARIMA model will be further tested against mineral demand projections, including scenarios that account for mineral supply from recycling. This will involve assessing a high-development scenario where significant advancements and improvements in recycling techniques are anticipated in the future. By incorporating these additional factors, the aim is to refine the projections and provide a more comprehensive and realistic forecast of mineral supply and demand dynamics.

The constant term represents the intercept of the model, which adjusts the baseline level of the forecast. An appropriate value of c ensures that the model aligns well with the average level of the historical data. The AR(1) term indicates the relationship between an observation and the previous observation. A properly calibrated AR(1) value helps in capturing the persistence or autocorrelation in the time series data, thereby improving the accuracy of the forecast.

Total Supply ARIMA model (kt)				
Mineral	2021	2030	2040	2050
Aluminum	57,404.78	66,812.91	81,885.63	98,585.81
Cadmium	26.43	27.23	28.63	30.15
Cobalt	183.40	206.51	261.18	336.18
Copper	21,749.92	25,746.36	30,204.72	34,770.58
Iron	4,518,988.70	4,764,340.89	5,708,036.61	7,138,204.25
Lead	6,380.78	6,754.80	7,884.84	8,492.11
Lithium	418.06	653.46	934.23	1,258.16
Nickle	2,357.17	2,814.83	3,366.04	4,167.33
REE	296.34	441.61	606.68	797.12
Zinc	16,564.50	18,928.59	22,486.55	26,099.38

Table 28. Total annual mineral supply forecast – ARIMA + High recycling scenario. Source: Own development

Total supply increase (absolute x times 2021)				
Mineral	2021	2030	2040	2050
Aluminum	1.0	1.2	1.4	1.7
Cadmium	1.0	1.0	1.1	1.1
Cobalt	1.0	1.1	1.4	1.8
Copper	1.0	1.2	1.4	1.6
Iron	1.0	1.1	1.3	1.6
Lead	1.0	1.1	1.2	1.3
Lithium	1.0	1.6	2.2	3.0
Nickle	1.0	1.2	1.4	1.8
REE	1.0	1.5	2.0	2.7
Zinc	1.0	1.1	1.4	1.6

Table 29. Annual mineral supply forecast increase – ARIMA + High recycling scenario. Source: Own development

The ARIMA model projections, under a high recycling scenario, indicate a significant overall increase in the supply of critical minerals by 2050. Key minerals such as aluminum, cobalt, copper, and lithium are expected to see substantial growth, driven by advancements in extraction technologies and enhanced recycling efforts. However, despite these increases, there remains a substantial risk that the supply may not be able to keep pace with the rapidly growing demand. Cobalt and lithium, in particular, show

marked increases in supply, yet their critical roles in battery technologies and renewable energy storage suggest that demand will outstrip supply. Other minerals like iron, nickel, and REEs also demonstrate significant growth, but their importance in industrial and technological applications further exacerbates the supply-demand gap. Minerals such as cadmium and lead show more modest increases, highlighting potential supply constraints and underscoring the need for continued innovation in sustainable practices. Hence, these projections underscore the necessity for ongoing investments in mining infrastructure and recycling technologies.

Finally, the results of the Hubbert curves for various minerals are presented in the following graphs. Additionally, summary tables displaying the parameters for the remaining minerals are provided below. Each model incorporates different variables as inputs, and some model curves are not displayed in the graphs below due to their unrealistic results and overestimated maximum output projections.

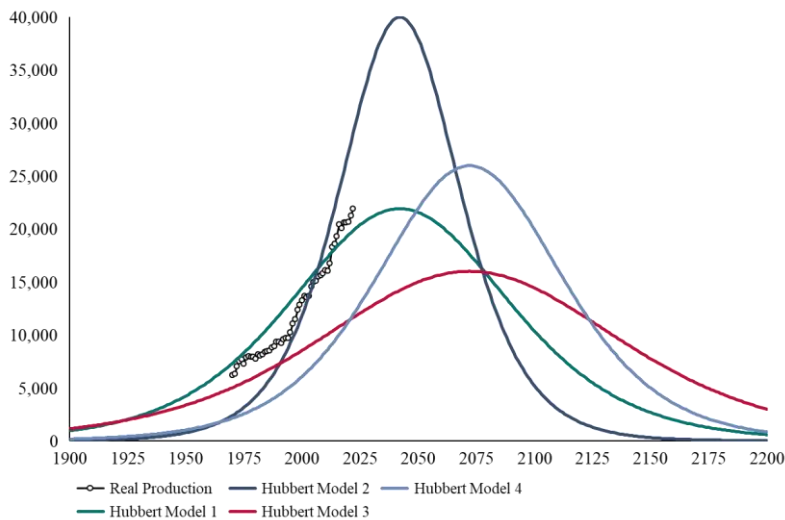


Figure 5.12. Copper Hubbert curves mineral production models. Source: Own development

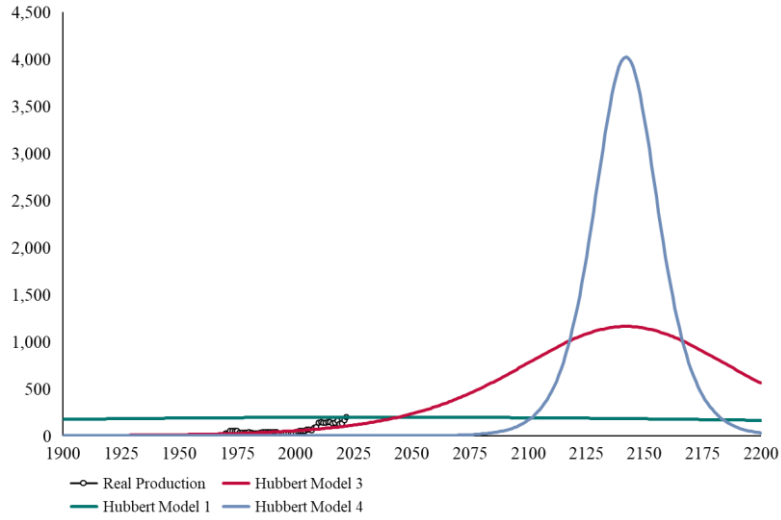


Figure 5.13. Cobalt Hubbert curves mineral production models. Source: Own development

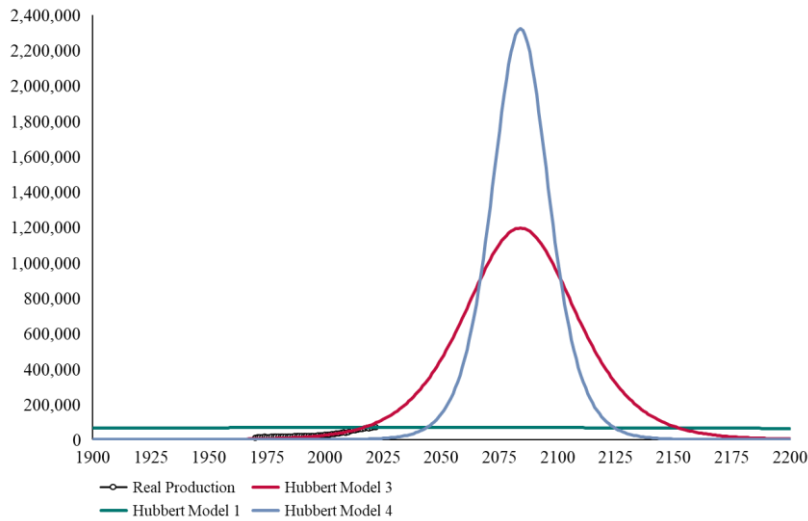


Figure 5.14. Aluminum Hubbert curves mineral production models. Source: Own development

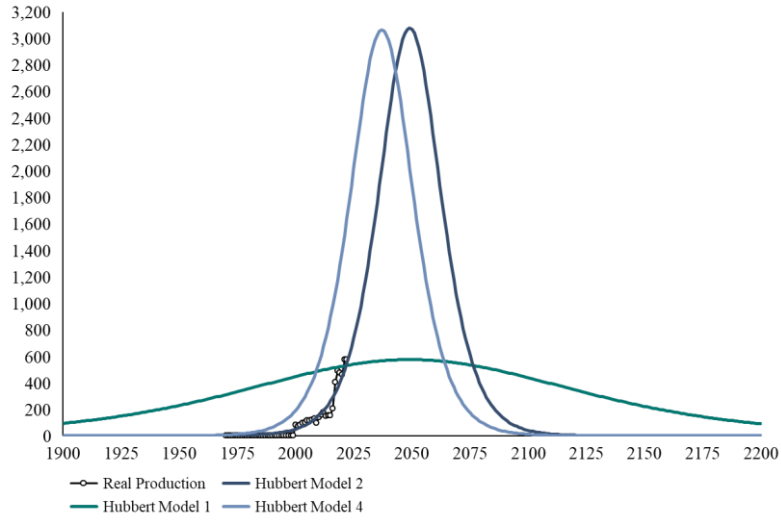


Figure 5.15. Lithium Hubbert curves mineral production models. Source: Own development

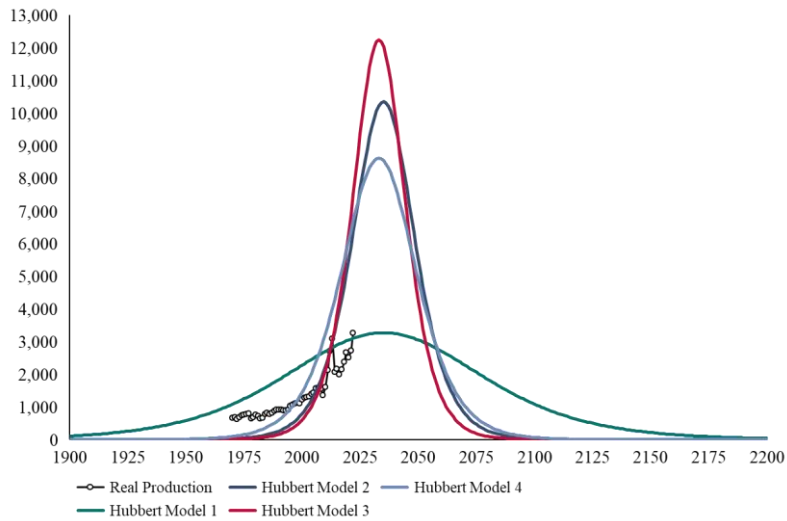


Figure 5.16. Nickle Hubbert curves mineral production models. Source: Own development

Hubbert model methodology					
Mineral	Peak time	b test 1	Pmax test 1	b test 2	Pmax test 2
Aluminum	2035	0.003573	68,400,000.00	0.29773	5,698,754,215
Cadmium	2035	0.015869	28,105.00	0.13159	233,063.97
Chromium	-	0.187986	42,200,000.00	-	-
Cobalt	2035	0.005310	197,000.00	0.28859	10,707,155.46
Copper	2042	0.031751	21,900,000.00	0.05795	9,972,614.71
Gallium	-	0.001702	427.00	-	-

Germanium	2035	0.001217	135.00	0.36849	40,871.00
Graphite	-	0.012137	2,613,409.00	-	-
Indium	-	0.058748	854.00	-	-
Iron	-	0.015759	3,457,825,285	-	-
Lead	2035	0.009695	5,320,740.00	0.17897	98,222,946.71
Lithium	2049	0.020886	575,046.70	0.11182	3,078,701.18
Manganese	-	0.145794	57,408,993.00	-	-
Molybdenum	-	0.145784	304,729.00	-	-
Nickel	2035	0.035339	3,270,000.00	0.11181	10,345,654.64
Phosphorus Rock	-	0.136895	272,068,587	-	-
PGM	-	0.124169	541,581.00	-	-
REE	2035	0.011569	300,000.00	0.24482	6,348,277.33
Silicon	-	-	-	-	-
Silver	-	0.130767	28,353,780.00	-	-
Tellurium	-	0.233989	633.00	-	-
Tin	-	0.110443	342,531.00	-	-
Tungsten	-	0.135149	92,515.00	-	-
Vanadium	2035	0.006399	105,000.00	0.24419	4,006,840.28
Zinc	2035	0.023036	3,629,556.00	0.10800	3,898,407.78

Table 30. Mineral production Hubbert curves coefficients. Source: Own development

Hubbert model methodology					
Mineral	Peak time	b test 3	Pmax test 3	b test 4	Pmax test 4
Aluminum	2084	0.0624	1,194,900,077	0.121	2,320,684,764
Cadmium	2082	0.0285	50,497.19	0.059	103,888.72
Chromium	2107	-	-	-	-
Cobalt	2142	0.0313	1,159,941.84	0.108	4,021,365.77
Copper	2072	0.0232	15,989,045.88	0.038	25,953,886.86
Gallium	2068	-	-	-	-
Germanium	2236	0.0224	2,482.82	0.131	14,496.27
Graphite	2148	-	-	-	-
Indium	2032	-	-	-	-
Iron	2091	-	-	-	-
Lead	2128	0.0219	12,046,210.45	0.070	38,529,965.72
Lithium	2037	0.2013	5,541,662.12	0.111	3,065,136.67

Manganese	2030	-	-	-	-
Molybdenum	2030	-	-	-	-
Nickel	2033	0.1321	12,226,682.75	0.093	8,614,112.46
Phosphorus Rock	2187	-	-	-	-
PGM	2075	-	-	-	-
REE	2160	0.0230	597,304.74	0.093	2,415,194.02
Silicon	-	-	-	-	-
Silver	2022	-	-	-	-
Tellurium	2062	-	-	-	-
Tin	2086	-	-	-	-
Tungsten	-	-	-	-	-
Vanadium	2124	0.0311	510,675.72	0.094	1,540,838.67
Zinc	2061	0.0360	21,299,469.26	0.056	32,942,477.68

Table 31. Mineral production Hubbert curves coefficients. Source: Own development

The results presented above indicate which models best align with the reality of mining production. They also provide insights into the projected peak extraction points and the rates at which production will increase. This analysis is crucial for understanding whether the estimated peak production can meet the rising annual demand driven by the Energy Transition and for determining the timeframe required to achieve these production rates, based on current reserves and identified resources.

The graphs highlight which models most accurately represent mineral supply. Specifically, model 2 appears to be the most accurate for copper, model 3 for cobalt and aluminum, model 2 for lithium, and model 2 for nickel. By examining the summary tables, one can extract the estimated peak production times to compare with projected demand. Additionally, a summary of ore supply, including future recycling estimates, is provided below. This summary will serve as a foundation for subsequent comparisons with mineral demand projections.

Total Supply Hubbert model (kt)				
Mineral	2021	2030	2040	2050
Aluminum	95,730.90	165,127.21	295,855.48	509,196.55
Cadmium	27.89	33.70	40.73	48.00
Cobalt	115.65	154.64	212.47	290.00

Copper	30,611.71	40,006.99	48,133.96	51,728.20
Iron	4,855,442.88	7,679,993.21	11,773,483.98	16,084,219.30
Lead	8,322.38	8,936.95	9,512.30	9,526.87
Lithium	494.50	1,179.14	2,439.61	3,173.04
Nickle	6,035.77	9,948.47	10,800.38	8,907.03
REE	91.31	113.78	144.59	182.64
Zinc	14,691.24	18,138.45	22,061.41	25,646.42

Table 32. Total mineral supply projections Hubbert curves – High recycling scenario. Source: Own development

Total supply increase (absolute x times 2021)				
Mineral	2021	2030	2040	2050
Aluminum	1.0	1.7	3.1	5.3
Cadmium	1.0	1.2	1.5	1.7
Cobalt	1.0	1.3	1.8	2.5
Copper	1.0	1.3	1.6	1.7
Iron	1.0	1.0	1.2	1.2
Lead	1.0	1.6	2.4	3.3
Lithium	1.0	1.1	1.1	1.1
Nickle	1.0	1.6	1.8	1.5
REE	1.0	1.2	1.6	2.0
Zinc	1.0	1.2	1.5	1.7

Table 33. Total mineral supply projections increase Hubbert curves – High recycling scenario. Source: Own development

5.3. Demand vs Supply

Comparing supply and demand mineral projections is crucial for several reasons. Firstly, it ensures that there is a clear understanding of whether future mineral supply can meet the anticipated demand, particularly in the context of the global Energy Transition and technological advancements. This comparison helps identify potential shortages and bottlenecks in the supply chain, which could hinder the development and deployment of renewable energy technologies, electric vehicles, and other critical industries. Furthermore, it provides valuable insights for policymakers, industry stakeholders, and

investors, enabling them to make informed decisions regarding resource management, investment in mining infrastructure, and the development of recycling technologies.

Below, graphs and tables comparing the total mineral supply with the demand required for the Energy Transition of the minerals studied in this thesis will be presented. This will be followed by a critical analysis of the results obtained and a comparison under two mineral supply trends, with an initial comparison against a linear trend.

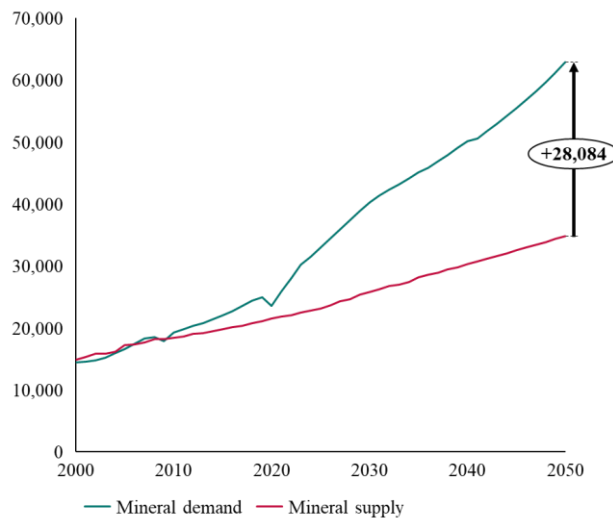


Figure 5.17. Copper demand vs supply (in kt) – STEPS, ARIMA, High recycling. Source: Own development

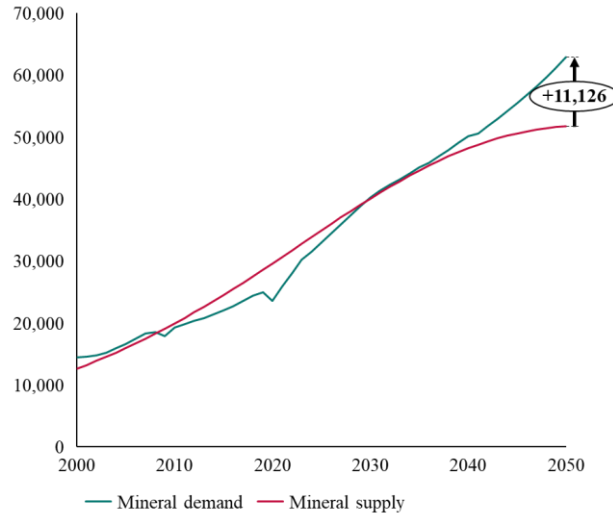


Figure 5.18. Copper demand vs supply (in kt) – STEPS, Hubbert, High recycling. Source: Own development

Based on the graphs comparing copper demand versus supply under the STEPS scenario with ARIMA and Hubbert models, along with a high recycling scenario, several qualitative and quantitative conclusions can be drawn. Quantitatively, the ARIMA model projects a significant shortfall in copper supply, with demand exceeding supply by approximately 28,084 kt by 2050. Despite the high recycling scenario, the supply growth is steady but insufficient, failing to match the sharply rising demand curve. In contrast, the Hubbert model forecasts a smaller but still considerable shortfall, with demand exceeding supply by 11,126 kt by 2050. The Hubbert model suggests a more responsive supply growth compared to the ARIMA model, yet it still falls short of meeting the escalating demand. Qualitatively, both models indicate that current and projected supply capacities, even with optimistic recycling improvements, are inadequate to meet future copper demand, highlighting critical supply constraints that need to be addressed to support the Energy Transition and associated technological advancements. The significant gaps between demand and supply emphasize the urgent need for technological innovations in copper extraction and recycling processes. Without such advancements, the industry will struggle to bridge the supply-demand gap. These findings suggest that policymakers must prioritize strategies to enhance mineral supply, including investing in mining infrastructure, supporting recycling technology development, and possibly

exploring alternative materials to mitigate supply risks. Furthermore, the smaller gap projected by the Hubbert model compared to the ARIMA model indicates that strategic planning and management of existing resources can somewhat alleviate supply shortages. However, comprehensive strategies involving both immediate actions and long-term plans are essential.

It is important to mention that the projected demand in the above comparison refers to the demand under a more conservative scenario, such as the STEPS. Consequently, more ambitious scenarios like the APS and the NZE scenario would likely present even greater challenges in terms of mineral production to meet the heightened demand. These scenarios, aimed at more aggressive decarbonization of the electricity and automotive sectors, would exacerbate the already significant supply-demand gaps identified in the STEPS scenario. This implies that under APS and NZE scenarios, the limitations in mineral production could be more pronounced, necessitating substantial advancements in extraction technologies, increased investment in mining infrastructure, and significant improvements in recycling processes. The urgency to develop and implement innovative solutions becomes even more critical to support the higher demand levels projected in these more ambitious pathways towards achieving global sustainability and decarbonization goals.

Finally, a comparative table is presented, juxtaposing the projected demand for 2030 and 2050 against the mineral supply under the STEPS scenario. This comparison utilizes Hubbert's supply modeling and assumes high breakthrough recycling capacities for all the minerals studied.

(kt)	2030		2050	
Mineral	Demand	Supply	Demand	Supply
Aluminum	94,495.86	165,127.21	183,513.69	509,196.55
Cadmium	30.15	33.70	39.86	48.00
Cobalt	869.21	154.64	2,019.22	290.00
Copper	40,273.50	40,006.99	62,864.15	51,728.20
Iron	1,947,690.76	7,679,993.21	3,159,257.67	16,084,219.30

Lead	18,810.25	8,936.95	52,440.61	9,526.87
Lithium	721.78	1,179.14	1,124.82	3,173.04
Nickle	6,324.08	9,948.47	11,025.89	8,907.03
REE	179.49	113.78	242.00	182.64
Zinc	22,630.38	18,138.45	44,192.20	25,646.42

Table 34. Demand vs Supply summary forecast results. Source: Own development

The comparative table highlights significant supply risks for several key minerals critical to the Energy Transition. Cobalt, copper, lead, nickel, and rare earth elements show pronounced supply deficits relative to projected demand by both 2030 and 2050. Despite improvements in recycling technologies and increased extraction efforts, the supply of these minerals falls substantially short of meeting the anticipated demand, particularly under the high growth scenarios associated with the Energy Transition. This discrepancy underscores the urgent need for further advancements in extraction and recycling technologies, as well as strategic resource management, to bridge the supply-demand gap and ensure the sustainable development of the energy and transportation sectors.

6. Conclusions

In a world where global warming and greenhouse gas emissions are escalating, new policies aim to promote the development of renewable technologies and achieve a low carbon footprint, envisioning an emission-free energy and transportation sector by 2050. Despite these efforts, a critical analysis of the mining sector's capacity to meet the mineral demand necessary for these energy policies has been overlooked. This study addresses this gap by projecting the intense mineral requirements of difficult-to-extract resources and identifying potential limitations, emphasizing the need for alternative solutions. By addressing these areas, the global community can better navigate the complexities of mineral supply and demand, ensuring that the Energy Transition is both sustainable and achievable.

Starting with the analysis of mineral intensity by technology and the projections for installed capacity in line with international decarbonization policies for 2050, this study has arrived at demand projections for key minerals such as cobalt, lithium, nickel, and copper, among others. These projections indicate a significant increase compared to current requirements, with demand surging by over 15 times in the most extreme net zero emissions scenarios by 2050. This stark increase underscores the critical role these minerals play in the Energy Transition, particularly in renewable energy technologies and electric vehicles.

Parallely, an in-depth analysis of current mining production capacity was conducted to understand whether future supply can meet this burgeoning demand under two distinct trends. First, under a linear increase in production, it was found that supply would quickly decouple from demand, creating a substantial gap. This gap would hinder the development of necessary technologies, ultimately failing to achieve a more sustainable world. Second, an exponential trend was modeled using Hubbert curves to project the maximum peak of mineral production and the timing of this peak. This model also considered scenarios of advanced mineral recycling development, highlighting the fundamental role recycling will play in maintaining supply levels close to demand.

Additionally, the study linked mineral demand to the energy required for extraction and the associated CO₂ emissions, revealing the hidden carbon footprint in current energy policies. Authorities often overlook the initial stages of the supply chain, which represent a significant share of global CO₂ and greenhouse gas emissions. The analysis shows that as mines become more exploited, the energy required to extract the same amount of ore increases, leading to a faster rate of energy consumption growth compared to mineral demand growth. This relationship highlights the increasing environmental and energy costs associated with maintaining and expanding mineral supply.

The findings indicate that under a worst-case recycling scenario and a Net Zero Emissions international policy scenario for 2050, mining production would become a bottleneck, impeding decarbonization efforts. Even in a conservative scenario with high technological progress in recycling, critical minerals such as copper, cobalt, nickel, lead, and rare earth elements remain limited in meeting projected demand.

In conclusion, energy policies need to integrate comprehensive strategies that address the entire mineral supply chain, from extraction to recycling. These strategies should focus on advancing extraction technologies, enhancing recycling processes, and ensuring sustainable supply chain management. Policymakers must also consider the environmental impact of mining and implement measures to mitigate associated CO₂ emissions. Future studies should monitor investment in the exploration and exploitation of key mineral deposits and project market prices against the costs of discovering and exploiting these resources. Balancing investment with the research and development of more mineral-efficient technologies is crucial. Economic signals, driven by market dynamics, play a fundamental role in guiding development and decision-making processes, even when aligned with challenging international sustainability objectives.

7. References

1. **United Nations Sustainable Development Goals:** United Nations Department of Economic and Social Affairs. Access on March 2024. Available at: <https://sdgs.un.org/goals>
2. **International Energy Agency - Minerals used in clean energy technologies compared to other power generation sources:** IEA. Access on March 2024. Available at: <https://www.iea.org/reports/the-role-of-critical-minerals-in-clean-energy-transitions/executive-summary>
3. **Wood Mackenzie - 700 Million Electric Vehicles Will Be on the Roads by 2050:** Wood Mackenzie. Access on March 2024. Available at: <https://www.woodmac.com/press-releases/700-million-electric-vehicles-will-be-on-the-roads-by-2050/>
4. **Energy International Agency - Today in Energy - Electric Vehicles:** U.S. IEA. Access on March 2024. Available at: <https://www.IEA.gov/todayinenergy/index.php?tg=%20vehicles>
5. **The European Commission - Raw Materials Information System:** European Commission, Joint Research Centre. Access on March 2024. Available at: <https://rmis.jrc.ec.europa.eu/>
6. **Copper Alliance - Stocks and Flows of Minerals Used in Clean Energy Technologies:** Copper International Alliance. Access on March 2024. Available at: https://www.copper.org/resources/market_data/infographics/copper-and-the-clean-energy-transition-brochure.pdf
7. **Thanatia. Límites materiales de la transición energética.** Alicia Valero et al. (2021)
8. **The Necessity of Recycling of Waste Li-Ion Batteries Used in Electric Vehicles as Objects Posing a Threat to Human Health and the Environment.** Agnieszka Sobianowska-Turek et al. (1 June 2021). Available at: <https://www.mdpi.com/2313-4321/6/2/35>
9. **Global energy consumption of the mineral mining industry: Exploring the historical perspective and future pathways to 2060.** Emmanuel Aramendia et al. (December 2023). Available at: <https://www.sciencedirect.com/science/article/pii/S0959378023001115>
10. **International Energy Agency - World Energy Outlook 2023:** IEA. Access on March 2024. Available at: <https://www.iea.org/reports/world-energy-outlook-2022>

11. **International Energy Agency - Global EV Outlook 2023:** IEA. Access on March 2024. Available at: <https://www.iea.org/reports/global-ev-outlook-2023>
12. **USGS Mineral Commodity Summaries (Production 2021-2022, Reserves and Resources):** United States Geological Survey. Access on March 2024. Available at: <https://pubs.usgs.gov/publication/mcs2022>
13. **BGS World Mineral Statistics (Production 1970-2020):** British Geological Survey. Access on March 2024. Available at: <https://www2.bgs.ac.uk/mineralsuk/statistics/worldStatistics.html>
14. **Copper distribution in European topsoils: An assessment based on LUCAS soil survey.** Cristiano Ballabio et al. (15 September 2018). Available at: from <https://www.sciencedirect.com/science/article/pii/S0048969718314451>
15. **S&P Global Market Intelligence (Production data):** S&P Global. Access on March 2024. Available at: <https://www.spglobal.com/commodityinsights/en/products-services/metals/market-data-metals>
16. **International Energy Agency - End-of-life recycling rates for selected metals:** IEA. Access on March 2024. Available at: <https://www.iea.org/data-and-statistics/charts/end-of-life-recycling-rates-for-selected-metals>
17. **EuRIC AISBL – Recycling: Bridging Circular Economy & Climate Policy:** Access on March 2024. Available at: https://circulareconomy.europa.eu/platform/sites/default/files/euric_metal_recycling_factsheet.pdf
18. **Time Series Analysis and Forecasting – Decision Support Models in the Electric Power Industry course.** Antonio Bello, 2022-23
19. **Energy International Agency – Global Critical Minerals Outlook 2024:** IEA. Access on May 2024. Available at: <https://iea.blob.core.windows.net/assets/ee01701d-1d5c-4ba8-9df6-abeecac9de99a/GlobalCriticalMineralsOutlook2024.pdf>

8. Annex I – Mining Production Data

Historical mining production data (t)					
Year	Aluminum	Cadmium	Chromium	Cobalt	Copper
1970	9,645,000	19,530	6,111,978	23,160	6,202,478
1971	10,266,000	18,375	6,356,676	24,357	6,278,422
1972	11,620,000	16,139	6,269,192	47,601	7,019,954
1973	12,745,000	17,492	6,791,334	49,330	7,477,898
1974	13,843,000	17,449	7,464,837	49,332	7,660,355
1975	12,744,000	15,632	8,386,332	50,300	7,241,592
1976	13,038,000	17,197	8,582,245	27,143	7,836,276
1977	14,337,000	18,634	9,340,481	27,091	7,940,945
1978	14,774,710	17,524	9,105,570	29,298	7,906,860
1979	15,185,960	18,841	9,212,998	31,807	7,912,257
1980	16,098,963	18,245	9,241,843	33,732	7,739,464
1981	15,697,358	17,214	8,865,768	28,612	8,162,994
1982	13,921,441	16,636	8,488,859	21,381	8,034,917
1983	14,359,961	17,598	8,207,725	19,597	8,113,058
1984	15,976,650	19,815	9,671,251	25,238	8,348,004
1985	15,591,568	19,371	11,220,819	30,391	8,409,241
1986	15,431,532	19,434	11,795,531	33,290	8,498,381
1987	17,713,406	19,263	11,759,527	35,776	8,786,976
1988	18,570,222	21,598	12,674,350	35,555	8,907,074
1989	19,099,419	21,197	14,470,488	35,035	9,334,657
1990	19,275,485	20,174	13,371,236	34,691	9,327,015
1991	19,752,516	21,133	13,972,182	33,299	9,196,933
1992	19,375,716	20,606	11,198,329	34,084	9,581,402
1993	19,757,358	19,469	9,473,471	24,906	9,667,947
1994	19,222,240	19,131	10,093,816	23,167	9,667,190
1995	19,904,179	20,161	14,231,763	27,008	10,238,121
1996	20,889,207	18,960	11,804,796	28,307	11,064,264
1997	21,952,226	20,275	13,903,059	29,024	11,472,831
1998	22,937,907	19,593	13,648,037	31,654	12,316,410
1999	23,912,156	19,991	14,677,252	31,773	12,797,343
2000	24,632,369	19,423	14,676,586	33,590	13,206,324
2001	24,692,106	18,599	12,180,810	44,065	13,652,544

2002	26,019,393	17,469	14,560,582	47,389	13,516,923
2003	28,047,987	25,187	16,037,569	46,465	13,637,943
2004	29,952,291	20,718	18,523,735	52,256	14,524,236
2005	31,902,673	19,640	19,394,548	59,592	14,958,389
2006	33,299,810	18,993	21,372,768	62,971	15,066,687
2007	38,209,038	18,540	25,006,204	57,968	15,502,548
2008	39,774,354	21,752	24,664,838	82,059	15,602,299
2009	37,083,029	20,767	19,996,492	87,210	15,803,948
2010	41,454,093	23,303	27,844,310	137,965	16,102,375
2011	46,654,557	21,210	26,040,045	145,182	15,989,615
2012	49,445,760	22,071	27,112,408	136,225	16,753,333
2013	52,222,635	22,374	30,867,291	137,850	18,295,037
2014	54,188,933	25,472	33,112,141	140,022	18,566,941
2015	57,866,798	24,988	30,519,265	144,384	19,290,301
2016	59,631,800	25,744	30,089,568	131,423	20,397,215
2017	62,645,575	24,765	33,905,586	135,810	20,026,902
2018	64,138,694	28,105	37,467,485	154,293	20,589,220
2019	62,919,121	26,811	38,924,787	123,153	20,569,688
2020	65,369,167	24,531	31,049,314	126,376	20,635,773
2021	67,500,000	24,700	42,200,000	165,000	21,200,000
2022	68,400,000	22,600	-	197,000	21,900,000

Historical mining production data (t)					
Year	Gallium	Germanium	Graphite	Indium	Iron
1970	-	62	391,168	-	766,398,000
1971	-	94	403,667	-	781,983,000
1972	-	72	380,070	-	774,797,000
1973	-	88	418,365	-	839,735,000
1974	-	113	498,301	-	891,893,000
1975	-	60	441,992	-	895,524,000
1976	-	51	410,601	-	903,206,000
1977	-	47	457,500	-	850,093,000
1978	-	48	505,079	-	847,492,000
1979	-	52	685,937	-	908,851,108
1980	-	69	572,234	-	896,750,439
1981	-	71	576,251	-	855,930,082

1982	-	54	548,148	-	815,810,731
1983	-	50	584,256	-	779,657,479
1984	-	50	600,025	-	880,269,854
1985	-	54	582,211	-	917,302,645
1986	-	54	634,223	-	931,928,777
1987	-	54	630,220	-	956,995,475
1988	-	49	672,057	-	976,464,674
1989	-	47	958,005	-	996,400,481
1990	-	48	1,141,001	-	983,950,118
1991	-	45	1,040,350	-	960,184,774
1992	-	42	998,074	-	934,599,458
1993	-	20	997,054	-	935,654,884
1994	-	13	1,296,600	-	996,033,060
1995	-	22	2,613,409	-	1,047,003,483
1996	-	53	2,364,958	-	1,022,338,732
1997	-	44	2,069,161	-	1,066,020,303
1998	-	37	2,035,394	-	1,054,983,712
1999	-	36	1,847,438	-	1,020,236,327
2000	-	39	2,031,555	-	1,089,648,315
2001	-	28	2,019,696	-	1,055,690,418
2002	-	26	1,615,968	-	1,122,961,514
2003	-	36	1,654,647	-	1,243,632,323
2004	-	35	1,757,969	-	1,381,885,081
2005	-	42	1,967,033	4	1,574,310,100
2006	-	107	2,081,872	629	1,838,099,879
2007	19	106	2,547,701	643	2,055,116,199
2008	39	107	2,380,188	627	2,237,708,530
2009	39	107	2,223,120	615	2,283,483,633
2010	37	122	2,128,707	643	2,635,427,769
2011	237	122	1,566,792	690	3,015,714,330
2012	314	126	1,172,142	726	2,972,651,682
2013	374	135	1,228,726	756	3,183,935,099
2014	351	135	1,281,763	796	3,457,825,285
2015	326	115	1,118,980	852	3,359,311,151
2016	222	90	972,546	798	3,319,465,492
2017	342	88	1,008,652	792	3,360,452,057

2018	427	104	1,137,064	804	2,945,188,705
2019	384	94	1,123,733	854	3,057,258,965
2020	372	93	958,392	818	3,015,931,162
2021	-	100	-	-	2,680,000,000
2022	-	100	-	-	2,600,000,000

Historical mining production data (t)					
Year	Lead	Lithium	Manganese	Molybdenum	Nickel
1970	3,350,380	-	19,737,454	137,417	663,376
1971	3,364,546	-	21,702,634	129,271	675,796
1972	3,469,178	-	20,876,364	134,973	627,908
1973	3,571,682	-	22,056,040	137,255	682,625
1974	3,578,914	-	23,050,505	143,001	737,791
1975	3,548,197	-	25,008,549	135,921	752,116
1976	3,475,866	-	25,033,133	172,218	774,915
1977	3,637,265	-	23,588,410	95,120	791,519
1978	3,601,401	-	23,243,104	100,112	641,524
1979	3,581,547	-	26,663,567	104,285	673,140
1980	3,547,515	-	27,081,019	110,100	758,352
1981	3,444,221	-	24,145,962	109,539	719,425
1982	3,524,979	-	24,311,055	95,031	633,493
1983	3,508,771	-	21,912,812	63,903	656,784
1984	3,448,759	-	25,170,576	97,941	768,060
1985	3,610,441	-	25,490,594	97,665	812,666
1986	3,342,461	-	25,505,943	93,846	785,136
1987	3,439,405	-	23,993,182	97,810	815,010
1988	3,186,010	-	25,035,621	112,585	874,213
1989	3,123,410	-	26,789,686	137,044	909,888
1990	3,142,758	-	26,699,523	126,800	906,016
1991	3,188,922	-	23,099,769	115,743	903,680
1992	3,016,614	-	22,250,590	108,583	889,367
1993	2,832,417	-	22,404,899	94,182	889,227
1994	2,747,462	-	21,355,303	108,676	908,303
1995	2,763,975	-	24,593,874	138,999	1,022,922
1996	3,065,827	-	25,197,750	130,236	1,061,732
1997	3,060,086	-	21,749,349	143,238	1,096,196

1998	3,039,041	-	19,859,761	139,763	1,130,608
1999	3,026,490	-	17,852,813	131,787	1,104,134
2000	3,051,684	80,244	20,014,560	135,761	1,226,506
2001	3,099,540	74,912	20,901,133	135,233	1,280,591
2002	2,866,318	80,725	22,638,616	124,620	1,291,550
2003	3,186,795	94,987	24,508,785	133,731	1,320,856
2004	3,194,841	100,716	28,587,809	160,802	1,389,830
2005	3,497,014	114,935	31,368,250	177,709	1,432,046
2006	3,582,859	115,133	32,870,417	189,427	1,562,209
2007	3,715,991	119,738	35,902,128	213,220	1,584,009
2008	3,819,384	129,254	38,485,504	219,123	1,551,053
2009	3,888,839	96,778	34,743,595	220,669	1,351,752
2010	4,360,026	136,950	45,212,584	245,070	1,605,130
2011	4,771,489	158,181	53,644,963	263,824	2,129,273
2012	5,113,128	179,159	53,564,045	275,572	2,709,476
2013	5,309,986	147,349	55,542,274	282,018	3,090,292
2014	5,320,740	155,675	55,035,932	304,729	2,074,365
2015	5,038,987	154,778	51,582,895	290,241	2,163,688
2016	4,858,175	206,909	50,754,916	284,320	1,993,057
2017	4,482,662	402,414	52,432,740	290,263	2,136,822
2018	4,471,639	491,953	54,825,029	289,425	2,383,865
2019	4,818,746	474,977	57,408,993	284,974	2,673,570
2020	4,543,981	462,340	49,583,771	297,361	2,510,131
2021	4,550,000	575,047	-	-	2,730,000
2022	4,460,000	575,047	-	-	3,270,000

Historical mining production data (t)					
Year	Phosphorus Rock	PGM	REE	Silicon	Silver
1970	81,910,398	131,940	-	-	9,286,153
1971	84,894,598	127,109	-	-	9,183,353
1972	91,357,999	131,109	-	-	9,175,849
1973	98,658,734	162,937	-	-	9,274,965
1974	107,551,139	179,811	-	-	8,956,690
1975	106,881,684	177,942	-	-	9,241,580
1976	107,688,240	186,161	-	-	9,734,989
1977	117,015,639	196,306	-	-	10,668,134

1978	124,727,109	197,078	-	-	10,888,673
1979	131,858,626	202,199	-	-	10,804,438
1980	143,984,799	212,893	-	-	10,764,732
1981	144,712,341	215,341	-	-	11,643,217
1982	127,440,952	210,881	-	-	11,970,998
1983	139,169,046	196,774	-	-	12,609,012
1984	152,925,031	226,192	-	-	13,046,457
1985	146,794,829	240,789	-	-	13,611,149
1986	140,754,013	263,027	-	-	13,255,297
1987	149,466,103	273,046	-	-	14,119,643
1988	158,821,358	281,596	-	-	14,236,380
1989	162,120,434	282,119	-	-	14,492,136
1990	159,130,106	291,561	-	-	14,828,230
1991	150,279,066	288,380	-	-	14,313,320
1992	140,458,725	265,672	54,895	-	14,492,233
1993	116,735,297	297,958	48,680	-	14,103,836
1994	128,094,710	344,806	57,002	-	13,744,028
1995	138,699,662	381,344	77,381	-	14,288,406
1996	142,678,468	428,045	84,740	-	14,982,506
1997	141,481,206	406,473	75,950	-	15,937,163
1998	143,178,694	459,130	82,553	-	16,542,395
1999	142,648,860	432,691	87,590	-	17,020,807
2000	132,476,901	443,966	80,300	-	18,202,193
2001	128,787,480	450,964	88,570	-	19,002,631
2002	138,996,600	386,315	96,340	-	18,904,408
2003	138,455,181	442,786	95,740	-	18,826,850
2004	145,064,625	514,880	103,082	-	19,891,031
2005	152,879,493	541,295	121,979	-	20,752,818
2006	151,180,177	520,534	137,180	-	20,207,038
2007	159,151,646	541,581	124,746	-	20,918,483
2008	164,465,695	475,441	127,682	-	21,436,885
2009	158,291,923	462,016	131,534	-	22,324,263
2010	180,118,750	481,124	121,027	-	23,391,198
2011	202,759,506	492,722	109,318	-	23,379,134
2012	219,199,242	442,774	106,791	-	25,035,925
2013	241,293,726	456,735	101,461	-	25,961,294

2014	240,017,515	377,655	150,767	-	27,434,650
2015	264,314,946	456,890	155,622	-	28,143,956
2016	272,068,587	452,977	163,900	-	28,132,810
2017	257,018,824	453,573	181,623	-	27,218,978
2018	232,591,896	469,202	253,297	-	28,006,638
2019	227,284,422	461,352	256,528	-	28,353,780
2020	221,165,901	430,419	264,439	-	24,563,120
2021	-	-	290,000	-	-
2022	-	-	300,000	-	-

Historical mining production data (t)					
Year	Tellurium	Tin	Tungsten	Vanadium	Zinc
1970	161	184,297	40,958	18,820	5,358,855
1971	145	186,263	45,722	17,123	5,390,196
1972	181	195,075	48,047	18,503	5,605,364
1973	201	186,236	49,569	19,571	6,006,463
1974	212	182,198	49,041	18,833	6,059,870
1975	155	227,607	48,329	25,845	6,172,015
1976	160	205,928	52,241	31,303	6,170,936
1977	202	211,724	41,208	31,216	6,468,985
1978	222	223,739	47,538	31,268	6,329,085
1979	217	226,047	48,975	34,670	6,273,902
1980	160	228,138	52,012	38,044	6,189,083
1981	175	231,776	50,046	34,851	6,124,683
1982	170	214,991	47,831	32,680	6,452,649
1983	170	194,256	43,150	27,993	6,660,533
1984	258	196,099	47,459	29,921	6,916,962
1985	245	187,650	49,480	31,681	7,102,048
1986	161	182,349	47,768	32,529	7,007,861
1987	115	183,429	40,716	31,943	7,245,132
1988	131	203,507	46,407	33,632	6,787,867
1989	136	222,951	51,900	34,868	6,870,155
1990	106	210,609	52,184	32,406	7,117,082
1991	136	193,325	48,268	29,478	7,316,422
1992	151	185,542	41,004	33,968	7,153,205
1993	141	185,877	34,395	30,393	6,729,080

1994	164	184,409	33,677	32,932	6,841,955
1995	225	198,006	37,589	42,646	7,080,783
1996	174	223,401	36,262	41,740	7,447,676
1997	159	221,516	34,526	43,390	7,427,711
1998	173	212,014	30,823	44,868	7,633,162
1999	166	220,062	26,696	36,012	8,084,693
2000	161	249,026	30,644	32,531	8,806,594
2001	159	244,295	35,143	33,678	9,103,312
2002	140	234,915	45,419	72,879	8,968,414
2003	149	257,041	48,031	60,965	9,567,043
2004	177	285,442	66,912	64,800	9,699,499
2005	117	297,812	60,619	64,604	10,116,144
2006	122	296,480	60,347	65,800	10,526,220
2007	140	342,531	58,360	65,486	11,224,590
2008	145	313,907	66,737	57,406	11,993,606
2009	152	314,539	63,310	56,689	11,641,802
2010	136	328,035	63,419	67,959	12,488,805
2011	220	327,237	73,025	71,502	12,525,080
2012	251	314,199	74,018	74,919	13,440,331
2013	298	297,916	76,651	81,391	13,617,077
2014	340	311,277	80,634	88,325	13,629,556
2015	324	315,571	83,011	89,129	13,413,387
2016	408	315,900	80,393	84,249	12,532,841
2017	430	336,887	83,573	84,864	11,925,400
2018	527	324,733	81,187	78,903	12,227,675
2019	620	310,661	90,400	95,021	12,483,251
2020	633	278,341	92,515	95,143	11,530,291
2021	-	-	-	105,000	12,700,000
2022	-	-	-	100,000	12,500,000

Table 35. Mineral historical mining production data (in t). Source: USGS & BGS

9. Annex II – Base Demand Models Results

	Model 1	Model 2	Model 3	Model 4	Model 5
Intercept	100.98383	21.61691	7.87611	7.51303	-26.23377
GDP	-	-	-	-	-
GDPc	-	0.00031	0.00033	0.00031	-
GDPg	-	-	-	-	-
POP	-	-	-0.00005	-0.00011	-0.00053
POPg	-	-	-	-	-
Urb Level	-	0.01292	-	0.01941	-
Year	-0.07074	-0.00726	-	-	-
LN(GDP)	-	-	-	-	-
LN(GDPc)	2.69559	-	-	-	2.93186
LN(GDPg)	-	-	-	-	-
LN(POP)	-	-	-	-	-
LN(POPg)	-	-	-	-	-
LN(Urb Level)	6.88077	-	-	-	3.46567
LN(Year)	-	-	-	-	-
R2	0.99091	0.99017	0.99017	0.99025	0.98910

	Model 6	Model 7	Model 8	Model 9	Model 10
Intercept	-14.38379	64.83196	-12.75486	-5.80204	-2.00500
GDP	-	-	-	-	-
GDPc	0.00033	-	-	-	-
GDPg	-	-	-	-	-
POP	-0.00019	-	-0.0004818	-	-
POPg	-	-	-	-	-
Urb Level	-	0.08912	0.08975	-	0.03781
Year	0.01155	-0.04032	-	-	-
LN(GDP)	-	-	-	-	-
LN(GDPc)	-	2.42932	2.41431	2.39277	2.38980
LN(GDPg)	-	-	-	-	-
LN(POP)	-	-	-	-1.69189	-1.26656
LN(POPg)	-	-	-	-	-

LN(Urb Level)	-	-	-	2.40482	-
LN(Year)	-	-	-	-	-
R2	0.99023	0.99126	0.99093	0.99041	0.99037

Table 36. Base demand forecast coefficients Aluminum. Source: Own development

	Model 1	Model 2	Model 3	Model 4	Model 5
Intercept	88.67398	53.39624	2.95196	2.31621	-17.67787
GDP	-	-	-	-	-
GDPc	-	0.00012	0.00015	0.00011	-
GDPg	-	-	-	-	-
POP	-	-	-0.00018	-0.00032	-0.00058
POPg	-	-	-	-	-
Urb Level	-	0.03559	-	0.03766	-
Year	-0.05671	-0.02649	-	-	-
LN(GDP)	-	-	-	-	-
LN(GDPc)	1.03947	-	-	-	0.95045
LN(GDPg)	-	-	-	-	-
LN(POP)	-	-	-	-	-
LN(POPg)	-	-	-	-	-
LN(Urb Level)	4.79021	-	-	-	4.09055
LN(Year)	-	-	-	-	-
R2	0.11029	0.10463	0.10383	0.10545	0.11015

	Model 6	Model 7	Model 8	Model 9	Model 10
Intercept	-350.63516	68.48222	-6.46607	5.13224	6.53335
GDP	-	-	-	-	-
GDPc	0.00009	-	-	-	-
GDPg	-	-	-	-	-
POP	-0.00229	-	-0.0004362	-	-
POPg	-	-	-	-	-
Urb Level	-	0.05589	0.05281	-	0.01876
Year	0.18347	-0.03926	-	-	-
LN(GDP)	-	-	-	-	-
LN(GDPc)	-	1.16293	1.07866	1.06925	1.15350
LN(GDPg)	-	-	-	-	-

LN(POP)	-	-	-	-2.01604	-1.69150
LN(POPg)	-	-	-	-	-
LN(Urb Level)	-	-	-	1.52464	-
LN(Year)	-	-	-	-	-
R2	0.10708	0.10927	0.10962	0.10946	0.10885

Table 37. Base demand forecast coefficients Cadmium. Source: Own development

	Model 1	Model 2	Model 3	Model 4	Model 5
Intercept	216.27246	74.23464	1.60148	0.32958	-84.51620
GDP	-	-	-	-	-
GDPc	-	0.00076	0.00074	0.00067	-
GDPg	-	-	-	-	-
POP	-	-	-0.00063	-0.00084	-0.00200
POPg	-	-	-	-	-
Urb Level	-	-0.04555	-	0.06769	-
Year	-0.15348	-0.03726	-	-	-
LN(GDP)	-	-	-	-	-
LN(GDPc)	6.68549	-	-	-	6.70983
LN(GDPg)	-	-	-	-	-
LN(POP)	-	-	-	-	-
LN(POPg)	-	-	-	-	-
LN(Urb Level)	8.92254	-	-	-	10.45478
LN(Year)	-	-	-	-	-
R2	0.86891	0.85980	0.86790	0.86884	0.87973

	Model 6	Model 7	Model 8	Model 9	Model 10
Intercept	-324.59752	178.25592	-47.54795	-12.70265	-12.84456
GDP	-	-	-	-	-
GDPc	0.00076	-	-	-	-
GDPg	-	-	-	-	-
POP	-0.00267	-	-0.0016632	-	-
POPg	-	-	-	-	-
Urb Level	-	0.13281	0.20275	-	0.00998
Year	0.16932	-0.11814	-	-	-
LN(GDP)	-	-	-	-	-

LN(GDPc)	-	6.17633	5.77892	5.59743	5.84926
LN(GDPg)	-	-	-	-	-
LN(POP)	-	-	-	-4.60921	-4.18302
LN(POPg)	-	-	-	-	-
LN(Urb Level)	-	-	-	1.63720	-
LN(Year)	-	-	-	-	-
R2	0.88042	0.87138	0.88682	0.87859	0.87813

Table 38. Base demand forecast coefficients Cobalt. Source: Own development

	Model 1	Model 2	Model 3	Model 4	Model 5
Intercept	206.97640	82.91967	12.44383	11.36886	-54.07356
GDP	-	-	-	-	-
GDPc	-	0.00046	0.00049	0.00043	-
GDPg	-	-	-	-	-
POP	-	-	-0.00042	-0.00059	-0.00171
POPg	-	-	-	-	-
Urb Level	-	0.01297	-	0.05672	-
Year	-0.13435	-0.03671	-	-	-
LN(GDP)	-	-	-	-	-
LN(GDPc)	3.91040	-	-	-	3.60824
LN(GDPg)	-	-	-	-	-
LN(POP)	-	-	-	-	-
LN(POPg)	-	-	-	-	-
LN(Urb Level)	10.49559	-	-	-	11.94198
LN(Year)	-	-	-	-	-
R2	0.97564	0.97581	0.98052	0.98313	0.96807

	Model 6	Model 7	Model 8	Model 9	Model 10
Intercept	-59.65397	151.72215	-15.22629	4.81587	8.98676
GDP	-	-	-	-	-
GDPc	0.00050	-	-	-	-
GDPg	-	-	-	-	-
POP	-0.00088	-	-0.0011919	-	-
POPg	-	-	-	-	-
Urb Level	-	0.13632	0.18166	-	0.04055

Year	0.03743	-0.08780	-	-	-
LN(GDP)	-	-	-	-	-
LN(GDPc)	-	3.48074	3.09315	3.23551	3.21975
LN(GDPg)	-	-	-	-	-
LN(POP)	-	-	-	-3.41603	-2.98445
LN(POPg)	-	-	-	-	-
LN(Urb Level)	-	-	-	2.51983	-
LN(Year)	-	-	-	-	-
R2	0.98236	0.97931	0.98807	0.97743	0.97688

Table 39. Base demand forecast coefficients Iron. Source: Own development

	Model 1	Model 2	Model 3	Model 4	Model 5
Intercept	-39.77428	-76.59106	7.39829	9.55576	-25.87590
GDP	-	-	-	-	-
GDPc	-	0.00041	0.00023	0.00035	-
GDPg	-	-	-	-	-
POP	-	-	-0.00006	0.00029	-0.00066
POPg	-	-	-	-	-
Urb Level	-	-0.18537	-	-0.11316	-
Year	0.02168	0.04544	-	-	-
LN(GDP)	-	-	-	-	-
LN(GDPc)	2.89421	-	-	-	2.79793
LN(GDPg)	-	-	-	-	-
LN(POP)	-	-	-	-	-
LN(POPg)	-	-	-	-	-
LN(Urb Level)	-5.38153	-	-	-	3.54205
LN(Year)	-	-	-	-	-
R2	0.89171	0.88907	0.86186	0.86733	0.90019

	Model 6	Model 7	Model 8	Model 9	Model 10
Intercept	-528.59443	-14.45638	-17.32514	-7.11032	-15.22202
GDP	-	-	-	-	-
GDPc	0.00027	-	-	-	-
GDPg	-	-	-	-	-
POP	-0.00345	-	-0.0002308	-	-

POPg	-	-	-	-	-
Urb Level	-	-0.07528	-0.02952	-	-0.07364
Year	0.27826	-0.00070	-	-	-
LN(GDP)	-	-	-	-	-
LN(GDPc)	-	3.14683	3.22877	2.99962	3.15954
LN(GDPg)	-	-	-	-	-
LN(POP)	-	-	-	0.53394	-0.09439
LN(POPg)	-	-	-	-	-
LN(Urb Level)	-	-	-	-4.05752	-
LN(Year)	-	-	-	-	-
R2	0.96213	0.89368	0.89856	0.89157	0.89380

Table 40. Base demand forecast coefficients Lead. Source: Own development

	Model 1	Model 2	Model 3	Model 4	Model 5
Intercept	-51.97868	-97.95925	5.22717	7.70160	-2.62270
GDP	-	-	-	-	-
GDPc	-	0.00033	0.00017	0.00030	-
GDPg	-	-	-	-	-
POP	-	-	0.00008	0.00052	0.00020
POPg	-	-	-	-	-
Urb Level	-	-0.16890	-	-0.13293	-
Year	0.02750	0.05517	-	-	-
LN(GDP)	-	-	-	-	-
LN(GDPc)	2.22226	-	-	-	2.17521
LN(GDPg)	-	-	-	-	-
LN(POP)	-	-	-	-	-
LN(POPg)	-	-	-	-	-
LN(Urb Level)	-4.14039	-	-	-	-2.88777
LN(Year)	-	-	-	-	-
R2	0.95534	0.95349	0.94569	0.95174	0.95497

	Model 6	Model 7	Model 8	Model 9	Model 10
Intercept	64.81081	-60.10895	-14.46279	-13.00319	-22.38803
GDP	-	-	-	-	-
GDPc	0.00017	-	-	-	-

GDPg	-	-	-	-	-
POP	0.00043	-	0.0002220	-	-
POPg	-	-	-	-	-
Urb Level	-	-0.10525	-0.09063	-	-0.08288
Year	-0.03091	0.02357	-	-	-
LN(GDP)	-	-	-	-	-
LN(GDPc)	-	2.78021	2.71779	2.68879	2.87057
LN(GDPg)	-	-	-	-	-
LN(POP)	-	-	-	1.49105	0.86633
LN(POPg)	-	-	-	-	-
LN(Urb Level)	-	-	-	-4.44223	-
LN(Year)	-	-	-	-	-
R2	0.94409	0.95979	0.95914	0.95903	0.96055

Table 41. Base demand forecast coefficients Nickle. Source: Own development

	Model 1	Model 2	Model 3	Model 4	Model 5
Intercept	218.96843	1,192.75581	10.18233	4.61257	-75.41916
GDP	-	-	-	-	-
GDPc	-	0.00136	0.00138	0.00132	-
GDPg	-	-	-	-	-
POP	-	-	-0.00199	-0.00439	-0.00145
POPg	-	-	-	-	-
Urb Level	-	0.95358	-	0.44458	-
Year	-0.15926	-0.61960	-	-	-
LN(GDP)	-	-	-	-	-
LN(GDPc)	12.04824	-	-	-	12.00782
LN(GDPg)	-	-	-	-	-
LN(POP)	-	-	-	-	-
LN(POPg)	-	-	-	-	-
LN(Urb Level)	0.07354	-	-	-	-3.79854
LN(Year)	-	-	-	-	-
R2	0.28244	0.28833	0.27737	0.28416	0.28241

	Model 6	Model 7	Model 8	Model 9	Model 10
Intercept	-785.22729	548.58322	-83.96349	58.29801	575.60513

GDP	-	-	-	-	-
GDPc	0.00133	-	-	-	-
GDPg	-	-	-	-	-
POP	-0.00677	-	-0.0021489	-	-
POPg	-	-	-	-	-
Urb Level	-	0.37888	0.06903	-	1.93287
Year	0.41261	-0.33036	-	-	-
LN(GDP)	-	-	-	-	-
LN(GDPc)	-	11.50543	11.45028	12.08205	11.64950
LN(GDPg)	-	-	-	-	-
LN(POP)	-	-	-	-25.13627	-87.30367
LN(POPg)	-	-	-	-	-
LN(Urb Level)	-	-	-	15.96897	-
LN(Year)	-	-	-	-	-
R2	0.28035	0.28446	0.28220	0.28784	0.30709

Table 42. Base demand forecast coefficients Zinc. Source: Own development

10. Annex III – Mineral Demand Forecast

Total demand (kt)				
Mineral	2021	2030	2040	2050
Aluminum	60,950.23	95,611.21	129,024.60	183,605.30
Cadmium	24.03	30.84	36.49	41.19
Cobalt	216.17	944.02	1,178.56	2,020.23
Copper	25,862.05	41,575.97	50,056.81	63,678.95
Iron	1,564,380.18	1,968,624.04	2,610,094.80	3,192,828.30
Lead	12,557.27	18,856.87	29,058.35	52,440.61
Lithium	161.65	797.82	848.27	1,135.82
Nickle	2,690.32	6,711.35	7,802.86	11,072.77
REE	79.48	188.69	213.67	252.79
Zinc	13,959.71	22,875.88	28,927.50	44,696.26

Table 43. Total annual mineral demand forecast – APS. Source: Own development

Total demand increase (absolute x times 2021)				
Mineral	2021	2030	2040	2050
Aluminum	1.0	1.6	2.1	3.0
Cadmium	1.0	1.3	1.5	1.7
Cobalt	1.0	4.4	5.5	9.3
Copper	1.0	1.6	1.9	2.5
Iron	1.0	1.3	1.7	2.0
Lead	1.0	1.5	2.3	4.2
Lithium	1.0	4.9	5.2	7.0
Nickle	1.0	2.5	2.9	4.1
REE	1.0	2.4	2.7	3.2
Zinc	1.0	1.6	2.1	3.2

Table 44. Annual mineral demand forecast increase – APS. Source: Own development

Total demand (kt)				
Mineral	2021	2030	2040	2050
Aluminum	60,950.23	95,660.96	129,131.42	183,628.58
Cadmium	24.03	31.57	37.96	41.60
Cobalt	216.17	945.39	1,180.35	2,021.22
Copper	25,862.05	42,181.83	51,149.21	63,903.37

Iron	1,564,380.18	2,000,326.35	2,653,997.19	3,199,230.53
Lead	12,557.27	18,856.87	29,058.34	52,440.61
Lithium	161.65	812.68	867.75	1,146.54
Nickle	2,690.32	6,744.24	7,867.81	11,090.47
REE	79.48	193.43	226.62	256.21
Zinc	13,959.71	23,097.70	29,541.53	44,850.54

Table 45. Total annual mineral demand forecast – NZS. Source: Own development

Total demand increase (absolute x times 2021)				
Mineral	2021	2030	2040	2050
Aluminum	1.0	1.6	2.1	3.0
Cadmium	1.0	1.3	1.6	1.7
Cobalt	1.0	4.4	5.5	9.4
Copper	1.0	1.6	2.0	2.5
Iron	1.0	1.3	1.7	2.0
Lead	1.0	1.5	2.3	4.2
Lithium	1.0	5.0	5.4	7.1
Nickle	1.0	2.5	2.9	4.1
REE	1.0	2.4	2.9	3.2
Zinc	1.0	1.7	2.1	3.2

Table 46. Annual mineral demand forecast increase – NZS. Source: Own development

11. Annex IV – Mineral Demand Segmented

Demand Segmented (kt)					
Year	Base	Energy	Hydrogen	Transport	Nuclear
2021	59,352.89	52.37	-	1,544.79	0.18
2022	62,471.83	65.17	-	2,435.65	0.80
2023	63,650.10	132.32	0.28	3,225.73	1.64
2024	66,289.64	132.26	0.26	4,014.75	1.64
2025	69,248.47	132.20	0.24	5,128.56	1.64
2026	72,258.97	132.15	0.23	5,929.14	1.64
2027	75,432.28	132.09	0.21	6,728.64	1.64
2028	78,775.98	132.03	0.20	7,527.07	1.64
2029	82,301.22	131.97	0.18	8,324.43	1.64
2030	84,924.69	131.92	0.16	9,437.44	1.64
2031	87,713.17	129.71	0.42	9,670.59	1.56
2032	90,630.00	129.71	0.41	9,903.66	1.56
2033	93,678.11	129.71	0.41	10,136.66	1.56
2034	96,867.63	129.71	0.40	10,369.58	1.56
2035	100,205.16	129.71	0.40	10,602.42	1.56
2036	103,514.41	97.80	0.28	10,835.20	1.43
2037	106,976.80	97.80	0.28	11,067.90	1.43
2038	110,596.06	97.80	0.27	11,300.52	1.43
2039	114,380.97	97.80	0.27	11,533.07	1.43
2040	118,346.13	97.80	0.27	11,765.55	1.43
2041	122,281.08	65.82	-	11,997.95	1.29
2042	126,398.05	65.82	-	12,230.28	1.29
2043	130,707.88	65.82	-	12,462.54	1.29
2044	135,223.49	65.82	-	12,694.72	1.29
2045	139,957.25	65.82	-	12,926.82	1.29
2046	145,181.41	65.82	-	13,158.85	1.29
2047	150,669.27	65.82	-	13,390.81	1.29
2048	156,437.90	65.82	-	13,622.69	1.29
2049	162,506.67	65.82	-	13,854.50	1.29
2050	168,896.58	65.82	-	14,550.00	1.29

Table 47. Aluminum mineral demand forecast segmented - STEPS. Source: Own development

Demand Segmented (kt)					
Year	Base	Energy	Hydrogen	Transport	Nuclear
2021	23.40	0.63	-	-	-
2022	23.92	1.68	-	-	-
2023	24.00	3.37	-	-	-
2024	24.31	3.41	-	-	-
2025	24.67	3.45	-	-	-
2026	25.03	3.49	-	-	-
2027	25.41	3.53	-	-	-
2028	25.81	3.57	-	-	-
2029	26.22	3.61	-	-	-
2030	26.50	3.65	-	-	-
2031	26.79	4.29	-	-	-
2032	27.10	4.38	-	-	-
2033	27.42	4.46	-	-	-
2034	27.76	4.54	-	-	-
2035	28.12	4.63	-	-	-
2036	28.49	4.46	-	-	-
2037	28.87	4.54	-	-	-
2038	29.27	4.62	-	-	-
2039	29.69	4.70	-	-	-
2040	30.13	4.78	-	-	-
2041	30.58	3.54	-	-	-
2042	31.06	3.59	-	-	-
2043	31.55	3.64	-	-	-
2044	32.07	3.70	-	-	-
2045	32.62	3.75	-	-	-
2046	33.20	3.80	-	-	-
2047	33.81	3.86	-	-	-
2048	34.46	3.91	-	-	-
2049	35.13	3.96	-	-	-
2050	35.84	4.01	-	-	-

Table 48. Cadmium mineral demand forecast segmented - STEPS. Source: Own development

Demand Segmented (kt)					
Year	Base	Energy	Hydrogen	Transport	Nuclear
2021	103.49	0.09	-	112.59	-

2022	114.81	0.68	-	176.90	-
2023	117.25	2.36	-	235.27	-
2024	125.51	2.36	-	293.06	-
2025	135.34	2.36	-	370.51	-
2026	146.11	2.36	-	428.00	-
2027	158.00	2.36	-	484.89	-
2028	171.14	2.36	-	541.18	-
2029	185.66	2.36	-	596.88	-
2030	195.88	2.36	-	670.97	-
2031	207.02	3.70	-	693.89	-
2032	219.15	3.70	-	717.08	-
2033	232.34	3.70	-	740.55	-
2034	246.71	3.70	-	764.29	-
2035	262.38	3.70	-	788.30	-
2036	279.36	3.61	-	812.59	-
2037	297.92	3.61	-	837.15	-
2038	318.20	3.61	-	861.98	-
2039	340.37	3.61	-	887.09	-
2040	364.72	3.61	-	912.47	-
2041	391.26	3.06	-	938.13	-
2042	420.43	3.06	-	964.05	-
2043	452.54	3.06	-	990.26	-
2044	487.96	3.06	-	1,016.73	-
2045	527.12	3.06	-	1,043.48	-
2046	570.75	3.06	-	1,070.50	-
2047	619.15	3.06	-	1,097.80	-
2048	672.93	3.06	-	1,125.37	-
2049	732.85	3.06	-	1,153.21	-
2050	799.76	3.06	-	1,216.40	-

Table 49. Cobalt mineral demand forecast segmented - STEPS. Source: Own development

Demand Segmented (kt)					
Year	Base	Energy	Hydrogen	Transport	Nuclear
2021	24,238.78	553.13	-	1,068.79	1.34
2022	25,065.41	1,206.90	-	1,694.08	5.92
2023	25,397.97	2,461.36	-	2,293.45	12.11
2024	26,090.81	2,462.63	-	2,894.65	12.11

2025	26,853.48	2,463.90	-	3,662.73	12.11
2026	27,642.14	2,465.17	-	4,278.66	12.11
2027	28,461.51	2,466.44	-	4,896.45	12.11
2028	29,312.38	2,467.71	-	5,516.11	12.11
2029	30,196.34	2,468.98	-	6,137.64	12.11
2030	30,866.56	2,470.25	-	6,924.58	12.11
2031	31,560.94	2,659.91	-	7,110.77	11.46
2032	32,279.13	2,651.32	-	7,297.26	11.46
2033	33,021.23	2,642.74	-	7,484.06	11.46
2034	33,788.89	2,634.16	-	7,671.18	11.46
2035	34,582.90	2,625.57	-	7,858.60	11.46
2036	35,399.07	2,354.52	-	8,046.33	10.54
2037	36,243.81	2,346.10	-	8,234.37	10.54
2038	37,117.33	2,337.67	-	8,422.72	10.54
2039	38,020.89	2,329.24	-	8,611.38	10.54
2040	38,956.89	2,320.81	-	8,800.35	10.54
2041	39,920.21	1,560.73	-	8,989.62	9.52
2042	40,917.72	1,555.00	-	9,179.21	9.52
2043	41,951.06	1,549.27	-	9,369.10	9.52
2044	43,022.20	1,543.54	-	9,559.31	9.52
2045	44,132.95	1,537.81	-	9,749.82	9.52
2046	45,292.14	1,532.08	-	9,940.64	9.52
2047	46,495.05	1,526.34	-	10,131.77	9.52
2048	47,743.90	1,520.61	-	10,323.21	9.52
2049	49,041.27	1,514.88	-	10,514.96	9.52
2050	50,389.90	1,509.15	-	10,955.58	9.52

Table 50. Copper mineral demand forecast segmented - STEPS. Source: Own development

Demand Segmented (kt)					
Year	Base	Energy	Hydrogen	Transport	Nuclear
2021	1,509,998.26	49,118.11	-	5,210.05	53.76
2022	1,565,909.61	55,032.19	-	8,198.47	236.79
2023	1,613,299.99	56,149.66	-	10,640.91	484.19
2024	1,696,468.91	56,303.44	-	13,084.63	484.19
2025	1,780,871.01	56,457.23	-	16,956.69	484.19
2026	1,829,009.77	56,611.01	-	19,446.40	484.19
2027	1,541,559.04	56,764.79	-	21,937.40	484.19

2028	1,772,848.60	56,918.58	-	24,429.70	484.19
2029	1,858,301.04	57,072.36	-	26,923.30	484.19
2030	1,859,167.34	57,226.14	-	30,813.09	484.19
2031	1,919,455.55	55,181.64	-	31,545.89	458.27
2032	1,990,333.79	55,220.99	-	32,278.92	458.27
2033	2,060,238.37	55,260.35	-	33,012.18	458.27
2034	2,133,892.20	55,299.70	-	33,745.66	458.27
2035	2,211,427.44	55,339.06	-	34,479.38	458.27
2036	2,293,109.89	51,075.94	-	35,213.32	421.40
2037	2,335,940.49	51,104.44	-	35,947.49	421.40
2038	2,382,859.88	51,132.95	-	36,681.89	421.40
2039	2,432,136.43	51,161.45	-	37,416.51	421.40
2040	2,483,734.20	51,189.95	-	38,151.37	421.40
2041	2,537,886.51	42,904.00	-	38,886.45	380.87
2042	2,594,681.96	42,922.21	-	39,621.76	380.87
2043	2,647,039.85	42,940.41	-	40,357.30	380.87
2044	2,702,040.84	42,958.62	-	41,093.06	380.87
2045	2,759,653.01	42,976.82	-	41,829.06	380.87
2046	2,820,019.27	42,995.03	-	42,565.28	380.87
2047	2,883,476.44	43,013.23	-	43,301.73	380.87
2048	2,942,071.46	43,031.44	-	44,038.41	380.87
2049	3,003,599.85	43,049.64	-	44,775.31	380.87
2050	3,068,239.52	43,067.85	-	47,569.43	380.87

Table 51. Iron mineral demand forecast segmented - STEPS. Source: Own development

Demand Segmented (kt)					
Year	Base	Energy	Hydrogen	Transport	Nuclear
2021	12,491.42	-	-	65.85	-
2022	13,155.70	-	-	103.67	-
2023	13,391.72	-	-	135.18	-
2024	13,952.12	-	-	166.70	-
2025	14,595.79	-	-	215.29	-
2026	15,291.20	-	-	247.36	-
2027	16,043.69	-	-	279.43	-
2028	16,858.49	-	-	311.50	-
2029	17,742.41	-	-	343.57	-
2030	18,417.94	-	-	392.31	-

2031	19,140.74	-	-	401.69	-
2032	19,915.16	-	-	411.08	-
2033	20,744.62	-	-	420.46	-
2034	21,635.16	-	-	429.84	-
2035	22,592.15	-	-	439.23	-
2036	23,622.01	-	-	448.61	-
2037	24,732.11	-	-	458.00	-
2038	25,928.71	-	-	467.38	-
2039	27,220.53	-	-	476.76	-
2040	28,619.40	-	-	486.15	-
2041	30,135.63	-	-	495.53	-
2042	31,781.14	-	-	504.91	-
2043	33,570.28	-	-	514.30	-
2044	35,519.92	-	-	523.68	-
2045	37,648.61	-	-	533.06	-
2046	39,977.74	-	-	542.45	-
2047	42,530.78	-	-	551.83	-
2048	45,335.60	-	-	561.21	-
2049	48,424.79	-	-	570.60	-
2050	51,836.11	-	-	604.50	-

Table 52. Lead mineral demand forecast segmented - STEPS. Source: Own development

Demand Segmented (kt)					
Year	Base	Energy	Hydrogen	Transport	Nuclear
2021	63.00	0.97	-	97.67	-
2022	68.00	7.34	-	154.18	-
2023	73.00	25.61	-	205.78	-
2024	75.43	25.61	-	257.32	-
2025	77.86	25.61	-	327.21	-
2026	80.29	25.61	-	379.53	-
2027	82.71	25.61	-	431.80	-
2028	85.14	25.61	-	484.02	-
2029	87.57	25.61	-	536.18	-
2030	90.00	25.61	-	606.17	-
2031	93.30	40.08	-	621.42	-
2032	96.60	40.08	-	636.67	-
2033	99.90	40.08	-	651.91	-

2034	103.20	40.08	-	667.15	-
2035	106.50	40.08	-	682.39	-
2036	109.80	39.17	-	697.62	-
2037	113.10	39.17	-	712.85	-
2038	116.40	39.17	-	728.07	-
2039	119.70	39.17	-	743.29	-
2040	123.00	39.17	-	758.50	-
2041	126.20	33.19	-	773.71	-
2042	129.40	33.19	-	788.92	-
2043	132.60	33.19	-	804.12	-
2044	135.80	33.19	-	819.32	-
2045	139.00	33.19	-	834.51	-
2046	142.20	33.19	-	849.70	-
2047	145.40	33.19	-	864.89	-
2048	148.60	33.19	-	880.07	-
2049	151.80	33.19	-	895.25	-
2050	155.00	33.19	-	936.63	-

Table 53. Lithium mineral demand forecast segmented - STEPS. Source: Own development

Demand Segmented (kt)					
Year	Base	Energy	Hydrogen	Transport	Nuclear
2021	2,114.94	22.71	-	551.49	1.18
2022	2,188.40	31.53	-	867.87	5.22
2023	2,220.63	66.68	0.45	1,161.57	10.66
2024	2,300.97	66.37	0.43	1,452.83	10.66
2025	2,391.74	66.06	0.41	1,832.15	10.66
2026	2,487.94	65.74	0.38	2,123.02	10.66
2027	2,589.98	65.43	0.36	2,411.40	10.66
2028	2,698.36	65.11	0.33	2,697.28	10.66
2029	2,813.57	64.80	0.31	2,980.67	10.66
2030	2,901.95	64.48	0.28	3,346.69	10.66
2031	2,994.50	69.51	0.71	3,424.02	10.09
2032	3,091.45	69.45	0.70	3,500.93	10.09
2033	3,193.15	69.40	0.70	3,577.44	10.09
2034	3,299.83	69.34	0.69	3,653.53	10.09
2035	3,411.82	69.29	0.69	3,729.21	10.09
2036	3,529.45	55.04	0.50	3,804.47	9.28

2037	3,653.08	55.00	0.49	3,879.33	9.28
2038	3,783.19	54.96	0.49	3,953.77	9.28
2039	3,920.21	54.92	0.49	4,027.80	9.28
2040	4,064.51	54.88	0.48	4,101.42	9.28
2041	4,216.64	39.04	0.01	4,174.63	8.39
2042	4,377.18	39.01	0.01	4,247.43	8.39
2043	4,546.74	38.99	0.01	4,319.81	8.39
2044	4,725.95	38.96	0.00	4,391.78	8.39
2045	4,915.51	38.93	0.00	4,463.34	8.39
2046	5,116.22	38.91	0.00	4,534.49	8.39
2047	5,328.96	38.88	0.00	4,605.23	8.39
2048	5,554.68	38.85	0.00	4,675.55	8.39
2049	5,794.42	38.83	-	4,745.47	8.39
2050	6,049.32	38.80	-	4,929.39	8.39

Table 54. Nickel mineral demand forecast segmented - STEPS. Source: Own development

Demand Segmented (kt)					
Year	Base	Energy	Hydrogen	Transport	Nuclear
2021	67.00	6.78	-	5.71	0.00
2022	71.50	8.56	-	9.00	0.00
2023	76.00	16.41	0.00	11.93	0.00
2024	83.29	16.56	0.00	14.85	0.00
2025	90.57	16.70	0.00	18.99	0.00
2026	97.86	16.85	0.00	21.97	0.00
2027	105.14	16.99	0.00	24.94	0.00
2028	112.43	17.14	0.00	27.92	0.00
2029	119.71	17.28	0.00	30.90	0.00
2030	127.00	17.43	0.00	35.06	0.00
2031	129.60	15.75	0.01	35.93	0.00
2032	132.20	15.78	0.01	36.80	0.00
2033	134.80	15.82	0.01	37.67	0.00
2034	137.40	15.85	0.01	38.54	0.00
2035	140.00	15.88	0.01	39.41	0.00
2036	142.60	11.62	0.01	40.28	0.00
2037	145.20	11.64	0.01	41.15	0.00
2038	147.80	11.66	0.01	42.02	0.00
2039	150.40	11.69	0.01	42.90	0.00

2040	153.00	11.71	0.01	43.77	0.00
2041	155.70	7.64	0.00	44.64	0.00
2042	158.40	7.65	0.00	45.51	0.00
2043	161.10	7.67	0.00	46.38	0.00
2044	163.80	7.68	0.00	47.25	0.00
2045	166.50	7.70	0.00	48.12	0.00
2046	169.20	7.71	0.00	48.99	0.00
2047	171.90	7.73	0.00	49.86	0.00
2048	174.60	7.74	0.00	50.73	0.00
2049	177.30	7.76	-	51.60	0.00
2050	180.00	7.77	-	54.22	0.00

Table 55. REE mineral demand forecast segmented - STEPS. Source: Own development

Demand Segmented (kt)					
Year	Base	Energy	Hydrogen	Transport	Nuclear
2021	13,636.33	323.38	-	-	-
2022	15,140.95	410.49	-	-	-
2023	14,306.76	800.40	-	-	-
2024	15,073.02	800.41	-	-	-
2025	16,121.07	800.42	-	-	-
2026	17,277.55	800.43	-	-	-
2027	18,555.84	800.44	-	-	-
2028	19,967.62	800.45	-	-	-
2029	21,529.93	800.47	-	-	-
2030	21,829.90	800.48	-	-	-
2031	22,177.90	753.92	-	-	-
2032	22,576.79	754.01	-	-	-
2033	23,024.53	754.09	-	-	-
2034	23,527.88	754.18	-	-	-
2035	24,089.13	754.26	-	-	-
2036	24,711.99	547.31	-	-	-
2037	25,402.47	547.39	-	-	-
2038	26,160.32	547.47	-	-	-
2039	26,991.21	547.55	-	-	-
2040	27,907.67	547.63	-	-	-
2041	28,913.58	350.78	-	-	-
2042	30,015.90	350.83	-	-	-

2043	31,224.39	350.89	-	-	-
2044	32,551.63	350.94	-	-	-
2045	34,010.04	351.00	-	-	-
2046	35,615.01	351.05	-	-	-
2047	37,380.08	351.10	-	-	-
2048	39,323.85	351.16	-	-	-
2049	41,468.84	351.21	-	-	-
2050	43,840.94	351.26	-	-	-

Table 56. Zinc mineral demand forecast segmented - STEPS. Source: Own development

12. Annex V –Extraction Energy Forecast

Energy extraction demand (mBOE)				
Mineral	2021	2030	2040	2050
Aluminum	192.61	327.32	497.11	765.57
Cadmium	0.04	0.05	0.06	0.08
Cobalt	0.84	3.69	5.98	10.31
Copper	136.85	224.12	311.95	437.70
Iron	108.21	148.03	217.57	293.62
Lead	7.69	12.63	21.52	42.36
Lithium	0.20	0.97	1.36	1.84
Nickle	9.01	23.16	33.33	48.95
REE	0.30	0.73	0.97	1.26
Zinc	8.83	15.51	21.84	37.48

Table 57. Energy demand forecast under STEPS scenario (in mBOE) – Low growth energy scenario.

Source: Own development

Energy extraction increase (absolute x times 2020)				
Mineral	2021	2030	2040	2050
Aluminum	1.00	1.70	2.58	3.97
Cadmium	1.00	1.24	1.56	2.02
Cobalt	1.00	4.40	7.14	12.31
Copper	1.00	1.64	2.28	3.20
Iron	1.00	1.37	2.01	2.71
Lead	1.00	1.64	2.80	5.51
Lithium	1.00	4.75	6.63	8.96
Nickle	1.00	2.57	3.70	5.43
REE	1.00	2.44	3.27	4.25
Zinc	1.00	1.76	2.47	4.24

Table 58. Energy demand forecast increase under STEPS scenario (in mBOE) – Low growth energy scenario. Source: Own development

Energy extraction demand (mBOE)				
Mineral	2021	2030	2040	2050
Aluminum	178.97	277.32	382.39	539.13
Cadmium	0.04	0.04	0.05	0.05

Cobalt	0.78	3.12	4.60	7.26
Copper	127.16	189.89	239.96	308.24
Iron	100.55	125.42	167.36	206.77
Lead	7.14	10.70	16.56	29.83
Lithium	0.19	0.82	1.04	1.29
Nickle	8.37	19.62	25.64	34.47
REE	0.28	0.61	0.75	0.89
Zinc	8.21	13.14	16.80	26.39

Table 59. Energy demand forecast under STEPS scenario (in mBOE) – Constant growth energy scenario.

Source: Own development

Energy extraction increase (absolute x times 2020)				
Mineral	2021	2030	2040	2050
Aluminum	1.00	1.55	2.14	3.01
Cadmium	1.00	1.13	1.29	1.53
Cobalt	1.00	4.01	5.91	9.33
Copper	1.00	1.49	1.89	2.42
Iron	1.00	1.25	1.66	2.06
Lead	1.00	1.50	2.32	4.18
Lithium	1.00	4.33	5.49	6.79
Nickle	1.00	2.34	3.06	4.12
REE	1.00	2.23	2.71	3.22
Zinc	1.00	1.60	2.05	3.22

Table 60. Energy demand forecast increase under STEPS scenario (in mBOE) – Constant growth energy scenario. Source: Own development

Energy extraction demand (mBOE)				
Mineral	2021	2030	2040	2050
Aluminum	223.24	444.25	746.24	1271.75
Cadmium	0.04	0.06	0.09	0.13
Cobalt	0.97	5.37	8.33	17.13
Copper	158.61	306.69	462.43	727.09
Iron	125.42	199.06	329.37	487.75
Lead	8.91	16.99	32.58	70.36
Lithium	0.24	1.43	1.86	3.05
Nickle	10.44	32.89	47.53	81.32

REE	0.34	1.00	1.44	2.10
Zinc	10.24	20.82	33.11	62.26

Table 61. Energy demand forecast under APS scenario (in mBOE) – High growth energy scenario.

Source: Own development

Energy extraction increase (absolute x times 2020)				
Mineral	2021	2030	2040	2050
Aluminum	1.00	1.99	3.34	5.70
Cadmium	1.00	1.44	2.03	2.90
Cobalt	1.00	5.53	8.58	17.65
Copper	1.00	1.93	2.92	4.58
Iron	1.00	1.59	2.63	3.89
Lead	1.00	1.91	3.66	7.90
Lithium	1.00	6.03	7.82	12.85
Nickle	1.00	3.15	4.55	7.79
REE	1.00	2.90	4.17	6.09
Zinc	1.00	2.03	3.23	6.08

Table 62. Energy demand forecast increase under APS scenario (in mBOE) – High growth energy scenario. Source: Own development

Energy extraction demand (mBOE)				
Mineral	2021	2030	2040	2050
Aluminum	192.61	331.03	492.25	765.57
Cadmium	0.04	0.05	0.06	0.08
Cobalt	0.84	4.00	5.50	10.31
Copper	136.85	228.53	305.04	437.70
Iron	108.21	148.33	217.26	293.62
Lead	7.69	12.66	21.49	42.36
Lithium	0.20	1.07	1.23	1.84
Nickle	9.01	24.51	31.35	48.95
REE	0.30	0.74	0.95	1.26
Zinc	8.83	15.51	21.84	37.48

Table 63. Energy demand forecast under APS scenario (in mBOE) – Low growth energy scenario.

Source: Own development

Energy extraction increase (absolute x times 2020)

Mineral	2021	2030	2040	2050
Aluminum	1.00	1.72	2.56	3.97
Cadmium	1.00	1.24	1.56	2.02
Cobalt	1.00	4.78	6.56	12.31
Copper	1.00	1.67	2.23	3.20
Iron	1.00	1.37	2.01	2.71
Lead	1.00	1.65	2.80	5.51
Lithium	1.00	5.21	5.98	8.96
Nickle	1.00	2.72	3.48	5.43
REE	1.00	2.50	3.19	4.25
Zinc	1.00	1.76	2.47	4.24

Table 64. Energy demand forecast increase under APS scenario (in mBOE) – Low growth energy scenario. Source: Own development

Energy extraction demand (mBOE)				
Mineral	2021	2030	2040	2050
Aluminum	178.97	280.47	378.65	539.13
Cadmium	0.04	0.04	0.05	0.05
Cobalt	0.78	3.39	4.23	7.26
Copper	127.16	193.62	234.64	308.24
Iron	100.55	125.67	167.12	206.77
Lead	7.14	10.73	16.53	29.83
Lithium	0.19	0.90	0.94	1.29
Nickle	8.37	20.76	24.12	34.47
REE	0.28	0.63	0.73	0.89
Zinc	8.21	13.14	16.80	26.39

Table 65. Energy demand forecast under APS scenario (in mBOE) – Constant growth energy scenario. Source: Own development

Energy extraction increase (absolute x times 2020)				
Mineral	2021	2030	2040	2050
Aluminum	1.00	1.57	2.12	3.01
Cadmium	1.00	1.13	1.29	1.53
Cobalt	1.00	4.35	5.43	9.33
Copper	1.00	1.52	1.85	2.42
Iron	1.00	1.25	1.66	2.06

Lead	1.00	1.50	2.31	4.18
Lithium	1.00	4.75	4.95	6.79
Nickle	1.00	2.48	2.88	4.12
REE	1.00	2.28	2.64	3.22
Zinc	1.00	1.60	2.05	3.22

Table 66. Energy demand forecast increase under APS scenario (in mBOE) – Constant growth energy scenario. Source: Own development

Energy extraction demand (mBOE)				
Mineral	2021	2030	2040	2050
Aluminum	223.24	444.26	746.25	1271.75
Cadmium	0.04	0.06	0.09	0.13
Cobalt	0.97	5.37	8.33	17.13
Copper	158.61	306.69	462.43	727.09
Iron	125.42	199.06	329.37	487.75
Lead	8.91	16.99	32.58	70.36
Lithium	0.24	1.43	1.86	3.05
Nickle	10.44	32.91	47.55	81.32
REE	0.34	1.00	1.44	2.10
Zinc	10.24	20.82	33.11	62.26

Table 67. Energy demand forecast under NZS scenario (in mBOE) – High growth energy scenario.

Source: Own development

Energy extraction increase (absolute x times 2020)				
Mineral	2021	2030	2040	2050
Aluminum	1.00	1.99	3.34	5.70
Cadmium	1.00	1.44	2.03	2.90
Cobalt	1.00	5.53	8.58	17.65
Copper	1.00	1.93	2.92	4.58
Iron	1.00	1.59	2.63	3.89
Lead	1.00	1.91	3.66	7.90
Lithium	1.00	6.03	7.82	12.85
Nickle	1.00	3.15	4.55	7.79
REE	1.00	2.90	4.18	6.09
Zinc	1.00	2.03	3.23	6.08

Table 68. Energy demand forecast increase under NZS scenario (in mBOE) – High growth energy scenario. Source: Own development

Energy extraction demand (mBOE)				
Mineral	2021	2030	2040	2050
Aluminum	192.61	331.04	492.25	765.57
Cadmium	0.04	0.05	0.06	0.08
Cobalt	0.84	4.00	5.50	10.31
Copper	136.85	228.53	305.04	437.70
Iron	108.21	148.33	217.26	293.62
Lead	7.69	12.66	21.49	42.36
Lithium	0.20	1.07	1.23	1.84
Nickle	9.01	24.52	31.36	48.95
REE	0.30	0.74	0.95	1.26
Zinc	8.83	15.51	21.84	37.48

Table 69. Energy demand forecast under NZS scenario (in mBOE) – Low growth energy scenario. Source: Own development

Energy extraction increase (absolute x times 2020)				
Mineral	2021	2030	2040	2050
Aluminum	1.00	1.72	2.56	3.97
Cadmium	1.00	1.24	1.56	2.02
Cobalt	1.00	4.78	6.56	12.31
Copper	1.00	1.67	2.23	3.20
Iron	1.00	1.37	2.01	2.71
Lead	1.00	1.65	2.80	5.51
Lithium	1.00	5.21	5.98	8.96
Nickle	1.00	2.72	3.48	5.43
REE	1.00	2.51	3.19	4.25
Zinc	1.00	1.76	2.47	4.24

Table 70. Energy demand forecast increase under NZS scenario (in mBOE) – Low growth energy scenario. Source: Own development

Energy extraction demand (mBOE)				
Mineral	2021	2030	2040	2050
Aluminum	178.97	280.48	378.65	539.13
Cadmium	0.04	0.04	0.05	0.05

Cobalt	0.78	3.39	4.23	7.26
Copper	127.16	193.62	234.64	308.24
Iron	100.55	125.67	167.12	206.77
Lead	7.14	10.73	16.53	29.83
Lithium	0.19	0.90	0.94	1.29
Nickle	8.37	20.78	24.13	34.47
REE	0.28	0.63	0.73	0.89
Zinc	8.21	13.14	16.80	26.39

Table 71. Energy demand forecast under NZS scenario (in mBOE) – Constant growth energy scenario.

Source: Own development

Energy extraction increase (absolute x times 2020)				
Mineral	2021	2030	2040	2050
Aluminum	1.00	1.57	2.12	3.01
Cadmium	1.00	1.13	1.29	1.53
Cobalt	1.00	4.35	5.43	9.33
Copper	1.00	1.52	1.85	2.42
Iron	1.00	1.25	1.66	2.06
Lead	1.00	1.50	2.31	4.18
Lithium	1.00	4.75	4.95	6.79
Nickle	1.00	2.48	2.88	4.12
REE	1.00	2.28	2.64	3.22
Zinc	1.00	1.60	2.05	3.22

Table 72. Energy demand forecast increase under NZS scenario (in mBOE) – Constant growth energy scenario. Source: Own development

13. Annex VI – Mineral Supply Forecast

Total Supply Hubbert model (kt)				
Mineral	2021	2030	2040	2050
Aluminum	95,397.17	163,670.51	291,364.01	497,653.71
Cadmium	27.76	33.30	39.88	46.53
Cobalt	114.79	151.78	206.03	277.81
Copper	30,468.86	39,444.11	46,652.66	48,703.11
Iron	4,834,231.13	7,588,583.45	11,499,859.74	15,420,509.70
Lead	5,045.58	6,080.28	7,425.27	8,986.38
Lithium	493.75	1,174.04	2,414.07	3,069.10
Nickle	6,028.82	9,902.12	10,582.04	8,159.69
REE	89.44	108.10	132.81	162.21
Zinc	14,603.15	17,850.61	21,429.79	24,517.54

Table 73. Total mineral supply projections Hubbert curves – Low recycling scenario. Source: Own development

Total supply increase (absolute x times 2021)				
Mineral	2021	2030	2040	2050
Aluminum	1.0	1.7	3.1	5.2
Cadmium	1.0	1.2	1.4	1.7
Cobalt	1.0	1.3	1.8	2.4
Copper	1.0	1.3	1.5	1.6
Iron	1.0	1.6	2.4	3.2
Lead	1.0	1.2	1.5	1.8
Lithium	1.0	2.4	4.9	6.2
Nickle	1.0	1.6	1.8	1.4
REE	1.0	1.2	1.5	1.8
Zinc	1.0	1.2	1.5	1.7

Table 74. Total mineral supply projections increase Hubbert curves – Low recycling scenario. Source: Own development

Total Supply Hubbert model (kt)				
Mineral	2021	2030	2040	2050
Aluminum	95,063.44	162,213.80	286,872.54	486,110.87
Cadmium	27.63	32.89	39.04	45.07
Cobalt	113.92	148.93	199.58	265.62
Copper	30,326.00	38,881.23	45,171.36	45,678.02
Iron	4,813,019.38	7,497,173.69	11,226,235.49	14,756,800.09
Lead	4,969.87	5,854.36	6,969.14	8,217.62
Lithium	493.75	1,174.04	2,414.07	3,069.10
Nickle	6,021.87	9,855.77	10,363.70	7,412.36
REE	89.44	108.10	132.81	162.21
Zinc	14,515.07	17,562.77	20,798.17	23,388.67

Table 75. Total mineral supply projections Hubbert curves – Constant recycling scenario. Source: Own development

Total supply increase (absolute x times 2021)				
Mineral	2021	2030	2040	2050
Aluminum	1.0	1.7	3.0	5.1
Cadmium	1.0	1.2	1.4	1.6
Cobalt	1.0	1.3	1.8	2.3
Copper	1.0	1.3	1.5	1.5
Iron	1.0	1.6	2.3	3.1
Lead	1.0	1.2	1.4	1.7
Lithium	1.0	2.4	4.9	6.2
Nickle	1.0	1.6	1.7	1.2
REE	1.0	1.2	1.5	1.8
Zinc	1.0	1.2	1.4	1.6

Table 76. Total mineral supply projections increase Hubbert curves – Constant recycling scenario. Source: Own development