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# Forecasting Rare Earth Element Demands for Clean Energy Technologies with the Bass Diffusion Model

Nehika Mathur<sup>a\*</sup>, Thomas Maani<sup>b</sup>, Chuanbing Rong<sup>c</sup>, John W. Sutherland<sup>b</sup>

<sup>a</sup>National Institute of Standards and Technology, 100 Bureau Dr, Gaithersburg, MD 20899, USA

<sup>b</sup>Environmental and Ecological Engineering, Purdue University, West Lafayette, IN 47906, USA

<sup>c</sup>Ford Motor Company, Dearborn, MI 48124, USA

\* Corresponding author. Tel.: +1-765-775-8216; fax: +0-000-000-0000. E-mail address: [nehika.mathur@nist.gov](mailto:nehika.mathur@nist.gov)

## Abstract

The push to decarbonize has spurred the demand for clean energy technologies such as electric vehicles (EVs) and wind turbines (WTs). These technologies rely on rare earth permanent magnets (REPMs), namely Neodymium-Iron-Boron (NdFeB) magnets that in turn rely on rare earth elements (REEs), including Neodymium (Nd), and Dysprosium (Dy). As the demand for clean energy technologies increases, so will the demand for Nd and Dy-containing REPMs. Both Nd and Dy are critical elements that are prone to supply chain risks. As our reliance on them increases, it becomes essential to anticipate future market dynamics for these elements. This paper aims to address the current gap in the literature in the context of forecasting future Nd and Dy demand quantities. The Bass Diffusion Model is a widely used approach to forecast the adoption of new products or technologies and, to predict demand trends. Over the years, the model has found applicability in a wide variety of sectors including consumer durables, medical services, and agricultural innovations. This paper demonstrates the use of the Bass Diffusion Model to estimate future global Nd and Dy demands, enabling a better understanding of swiftly evolving clean energy technology and REPM-related market dynamics.

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## 1. Introduction

Aligned with meeting the goals of the Paris Climate Accord Agreement and in response to the Intergovernmental Panel on Climate Change (IPCC) Assessment Report (AR) 6 that calls for “deep, rapid and sustained global Greenhouse Gas (GHG) reduction this decade” nations across the globe are transitioning to clean energy technologies [1, 2]. This requires implementing technological interventions to reduce our reliance on fossil fuels, particularly in the energy and transportation sectors, two economic sectors that together account for more than 50% of total GHG emissions [3]. Unlike conventional fossil-fuel based technologies, the environmental impacts across the ‘use phase’ of clean energy technologies such as solar photovoltaics (PVs), wind turbines (WTs), and electric vehicles (EVs) is significantly lower [4]. Clean energy

technologies rely on renewable resources and thus contribute towards energy security as well.

However, the transition to a decarbonized economy via the implementation of clean energy technologies remains tenuous. This is because the production of many clean energy technologies depends on the consistent supply of critical materials. For instance, fast-growing WT and EV industries (Figure 1) depend on the steady production and supply of rare earth elements (REEs), Neodymium (Nd) and Dysprosium (Dy). Both Nd and Dy are obtained upon purification from mining their respective Rare Earth Oxide (REO) forms, (Nd<sub>2</sub>O<sub>3</sub> and Dy<sub>2</sub>O<sub>3</sub>). Nd and Dy are materials that go into producing Neodymium-Iron-Boron (NdFeB) Rare Earth Permanent Magnets (REPMs), components that are critical for manufacturing WT generators and EV traction motors. According to Mancheri et al. (2019) REPMs, batteries, catalysts, and phosphors presently account for more than 60 %

of REO demand and this demand will continue to grow rapidly driven primarily by the growing sales of clean energy technology products [5]. Over the years, REPMs have been and continue to be used in numerous applications, ranging from appliances and computers to high end motors and generators for clean energy products [6]. This is because of their higher energy density and coercive forces when compared to ferritic magnets. Thus, smaller REPMs can be used in place of larger ferrite magnets for meeting similar functions [6].

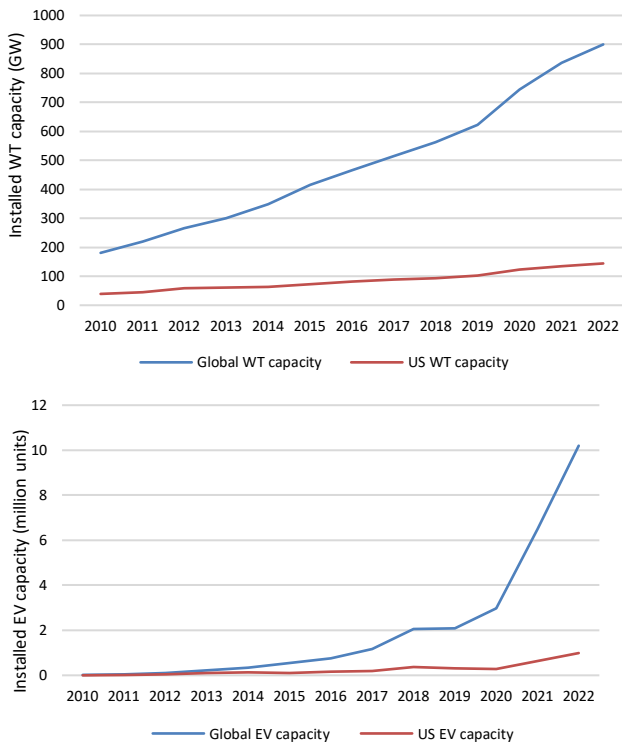


Figure 1: WT and EV capacities (2010 – 2022) [7]

Table 1: Nd and Dy concentrations in REPMs based on application [adapted from 6, 8, 9]

Applications	Nd content (%)	Dy content (%)	Magnet weight/unit (g/unit)
WTs	30	4.5	500,000 – 700,000
EVs	24-30	0-5	1,000 - 2,000
Washing machines	28	3	100 - 250
Refrigerators	28	3	100 - 250
MRIs	31	0	150 - 200
Air conditioners	28	3	100 - 250
Motors (general auto)	26-27	4-5	34
Desktop computers	29.5 - 30	1 - 1.5	10
Laptop computers	29.5 - 30	1 - 1.5	2

Maintaining a steady supply of Nd and Dy to fulfill the rapidly increasing demands for REPMs is particularly challenging. This is because there is a strong requirement to sustain the growth of WTs and EVs, to meet the broader decarbonization goals. Unlike other REPM consuming applications, the concentration of Nd and Dy used in REPMs in WTs and EVs is significantly higher (Table 1). Moreover, the production of Nd and Dy has been and remains to be dominated by China which is not only rich in REE reserves but also possesses strong refining capabilities [6, 10]. REE mining is extremely resource and environmentally intensive. Consequently, many countries endowed with domestic REE reserves opt not to engage in large-scale REE production due

to their robust environmental regulations. Instead, they lean towards sourcing their REE supplies from China. This scenario has further reinforced China's continued dominance in the global REE market (see Figure 2). The uncertainties associated with this combination of factors may make the adoption and subsequent planning for the transition to clean energy technologies difficult for manufacturers particularly automotive and energy companies as well as other governmental and non-governmental stakeholders [6, 10].

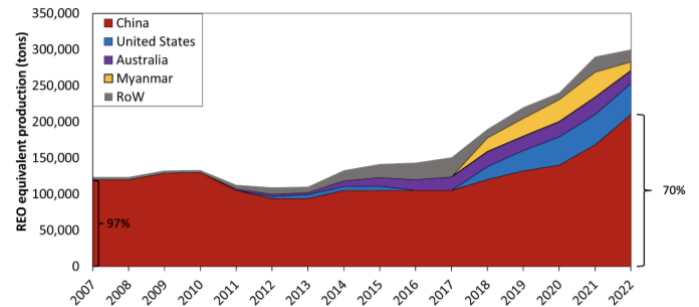


Figure 2: Shares of REO-equivalent production [adapted from 6]

Understanding the historical and current market trends, while being able to accurately anticipate the future market dynamics surrounding these new technologies will be beneficial as sustainable development becomes a more ubiquitous part of national agendas. By extension, this means that a better understanding of the market parameters associated with REEs may be required so that manufacturers, policy makers and other stakeholders can effectively strategize and implement realistic decarbonization goals. Anticipating future REE demand is one component of understanding overall REE and clean energy technologies market dynamics. Unfortunately, individual REE demand numbers are limited because clean energy technologies such as WTs and EVs are themselves novel and their potential to and the speed at which they will penetrate the market remains unclear. Additionally, the complex geopolitical situation surrounding the raw material feedstocks, namely REEs, that go into producing REPMs for WTs and EVs only contributes to further increasing the uncertainty related to determining current and future market dynamics.

This paper addresses the limited data on Nd and Dy demand trends over the next few decades. The main contributions of this paper are:

- A survey of the literature to glean historical and future Nd and Dy demand estimates, if any.
- The identification of a suitable forecasting method via the review of widely used commodity forecasting methods available in the scientific literature.
- The application of the identified forecasting method, i.e., the Bass Diffusion Model to estimate Nd and Dy demands till 2050.

The paper is structured in the following manner: The result from the literature reviewed (Section 2) confirms the uncertainty associated with REE market parameters. Section 2 also reviews different diffusion models for the purposes of computing sales or demand data for new products. Section 3 describes the Bass Diffusion Model and its application to estimating Nd and Dy demand data till 2050. This is followed

by the results (Section 4) and a summary and outlook (Section 5).

**2. Literature Review**

The literature suggests tremendous uncertainty associated with REE market parameters. Although the demand for REEs was strong during the 1960s (as color TVs became popular), it spiked by the turn of the century. It is estimated that in 1953, REO demand was 1000 tons valued at about US\$ 25 million [11]. By 1997 REO demand had grown to 66 thousand tons and was up to 125 thousand tons in 2008 [12]. Other studies however estimate REO demand to be lower (~118 thousand in 2014 and 170 thousand by 2020) [13]. Similarly, studies have attempted to determine the rate of REO demand growth. Kingsnorth (2016) believes that the demand for REEs will steadily grow at the rate of 7-8% annually, in contrast to Alonso et al. (2012) who has earlier predicted the annual rate of growth at around 5% by 2020 for REEs [14, 15]. Additionally, there is limited information on the application-specific demand for REPMs. We identified two studies [8, 9] that estimated these demand numbers using top-down or bottom-up approaches that rely on production data, import/export data, and several assumptions based on historical data and projections. The disparity in forecasts for REE market parameters makes it difficult for stakeholders to anticipate the REE market to plan and strategize for the future.

Diffusion models have been used extensively to estimate new product penetration in the market. The diffusion of an innovation is the process via which the innovation gets communicated through certain channels over a given period within a given social system [16, 17]. Diffusion processes are typically characterized by an S-shaped curve and have been used to mathematically represent spread of new technologies and services. The most widely applied diffusion models are the Bass, the Logistic and the Gompertz models [18, 19]. No clear consensus exists as to which diffusion model is the best performing. In their study, Young and Ord (1989) developed a framework to test and compare the performance of the Logistic and Gompertz curves, but the results of their trials remained inconclusive [20]. Building upon this work, Young (1993) included the Bass model in a subsequent study and concluded the Bass model did outperform the other two models when the upper limit of the market was not known [21]. Subsequently, however, in the context of understanding the development of the telecommunication market across different nations, Meade and Islam (1995) observed that the Bass model was outperformed by the Logistic and Gompertz models [22]. More recently and considering the growing demand for clean energy technologies studies that analyze their uptake and growth trends have been carried out using the Bass Diffusion Model [23-28].

It should be noted that unlike the internal influence-driven Logistic and Gompertz models, the Bass model is a mixed influence model that accounts for both internal (word-of-mouth communication) and external (impact of mass media advertising) influences. Interestingly, the Bass Diffusion Model may be well suited to analyze the clean energy technology and REE market for a few reasons. One main

advantage of the Bass Diffusion Model is its robustness while requiring limited data [29]. In addition, Naseri and Elliott (2013) observe that heterogeneity associated with innovativeness (first adopters versus others) coupled with income heterogeneity (as the price of the new product falls, more individuals can afford it) further reinforces the S curve [30]. Moreover, income disparity across society (represented by the Gini coefficient) is positively correlated with the ratio of imitation to innovation used by the Bass Model [31]. Thus, in summary based on the literature reviewed and owing to the lack of data on future demands of REEs, the robustness of the Bass Diffusion model and its ability to capture both external and internal influences, this paper applies the Bass model for forecasting global Nd<sub>2</sub>O<sub>3</sub> and Dy<sub>2</sub>O<sub>3</sub> demands until 2050.

**3. Method**

As mentioned previously, the Bass model is a mixed influence model that combines two basic models into one generalized model, thus capturing the impacts of both innovation and imitation on the diffusion process of a new product in a market [17, 30, 32]. The model divides the market distinctly into innovators and imitators, where innovators are assumed to be independent actors who are not impacted in their decision to adopt a new product by the actions of other members in the market (Figure 3). Innovators acquire information on the new product via mass media and other forms of formal advertisement. In contrast, imitators are influenced by the other actors in a market and gather their information because of word-of-mouth and other informal channels. Aligned with Roger’s theory of diffusion, the Bass model assumes that the impact of advertisement is greater early on, i.e., when the product is first introduced, whereas the impact of word-of-mouth communication is greater at the later stages of the diffusion process [33].

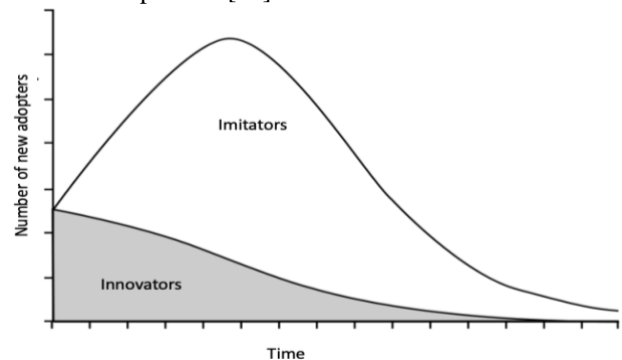


Figure 3: The Bass Diffusion Model (adapted from Bass, 1969 [32])

Mathematically, the Bass Diffusion Model is expressed as:

$$f(t) = (p + qF(t))(1 - F(t)) \tag{1}$$

$$f(t) = a(t)/N \tag{2}$$

$$F(t) = A(t)/N \tag{3}$$

Where,

$f(t)$ , density function of sales at time  $t$

$a(t)$ , product purchase rate at time  $t$

$F(t)$ , cumulative fraction of potential growth at time  $t$

$A(t)$ , total number of adopters at time  $t$

$N$ , total number of potential buyers  
 $p$ , coefficient of innovation  
 $q$ , coefficient of imitation

Based on Eq. (1), the diffusion adoption trend of a new product depends on market size,  $N$ , and the values of the coefficients of innovation and imitation,  $p$  and  $q$  respectively. It should be noted that some studies express demand in the form of REEs, i.e., pure Nd and Dy, while other studies express demand in the form of REOs, namely  $Nd_2O_3$  and  $Dy_2O_3$ .

This study estimated  $Nd_2O_3$  and  $Dy_2O_3$  demands using the Bass Diffusion model and subsequently uses stoichiometric conversion factors available in the literature to estimate pure Nd and Dy demands (see Appendix A). Using the mean demand estimates available in the literature from 2008 to 2030 for  $Nd_2O_3$  and from 2009 to 2030 for  $Dy_2O_3$  (see Appendix A) [34, 35, 36], the mean demand projections for both REOs using curve fitting and optimizing the Bass Model  $p$  and  $q$  values were determined.  $N$ , the total number of potential buyers was based on the potential number of EV buyers [36]. A range of demand values has been generated. High and low demands for both  $Nd_2O_3$  and  $Dy_2O_3$  were based on Monte Carlo trials for the number of adopters,  $N$  within one standard deviation of  $N$ .

#### 4. Results and discussion

$Nd_2O_3$  and  $Dy_2O_3$  demand data was collected from the literature for the timeframe 2008 - 2030 [34, 35]. The mean market size is assumed to be 50 million with  $N$  ranging anywhere from 33 million to 67 million for low and high demand scenarios respectively [37]. The coefficients  $p$  and  $q$  were determined using this limited dataset for both  $Nd_2O_3$  and  $Dy_2O_3$  and by applying Eq. (1) (See Table 2). By substituting the values of  $p$ ,  $q$ , and  $N$  in equations 1 through 3, the demand estimates for both REOs were generated till 2050 (Figure 4).

Table 2: Bass parameters used in estimating  $Nd_2O_3$  and  $Dy_2O_3$  demands

REO	Demand scenario	N (million units)	p	q
$Nd_2O_3$	Low	33	2.72E-04	0.123
	Mean	50		
	High	67		
$Dy_2O_3$	Low	33	5.53E-05	0.054
	Mean	50		
	High	67		

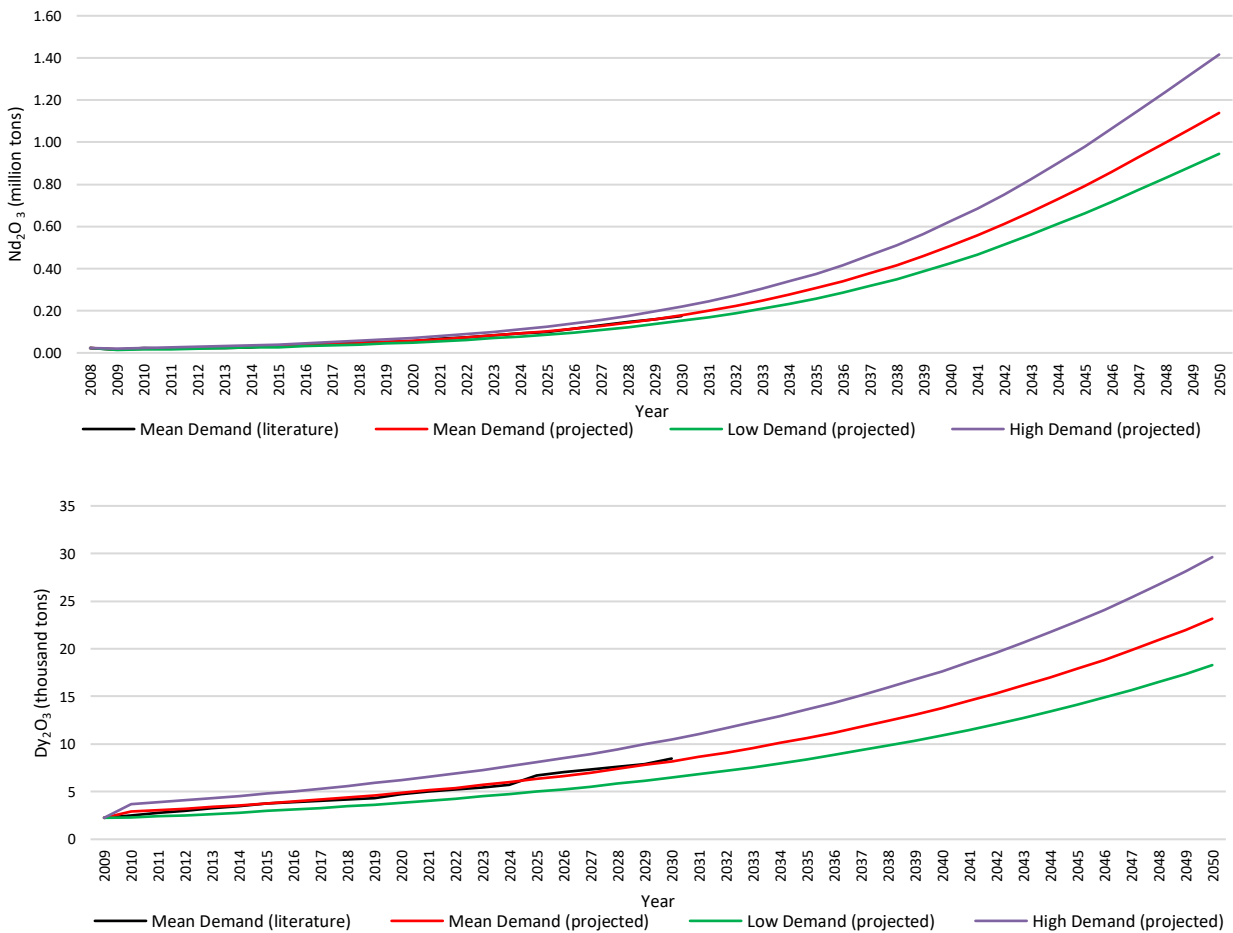


Figure 4:  $Nd_2O_3$  and  $Dy_2O_3$  Bass Diffusion Model global demand trends till 2050 under low, mean, and high market size scenarios

On average the model indicates that Nd demand will be up by more than 4600 % up by 2050 from its 2008 levels. Per current estimates, Dy demand will also rise significantly. On average, Dy demand will be up by 1027 % by 2050 from its 2009 level. In a high demand scenario, the Bass model indicates that this number could be as high as 1200 % in 2050. This forecast is representative of global Nd and Dy demand across a

number of REPM consuming applications and is based on very limited historical and forecasted data from literature. As mentioned earlier, one of the challenges associated with estimating future REE market parameters is the lack of disaggregated data. More granular data such as application-specific historical demands and county and/or region-wise historical demands for Nd and Dy would enable a more

accurate assessment of future Nd and Dy demands.

Table 3: Mean Nd and Dy demand forecasts

Year	Mean Nd demand (tons)	Mean Dy demand (tons)
2008	20,482.30	-
2009	14,161.94	1,966.36
2010	15,894.46	2,514.81
2011	17,837.57	2,649.93
2012	20,016.50	2,792.30
2013	22,459.43	2,942.30
2014	25,197.77	3,100.34
2015	28,266.54	3,266.84
2016	31,704.72	3,442.25
2017	35,555.65	3,627.06
2018	39,867.48	3,821.76
2019	44,693.58	4,026.87
2020	50,093.07	4,242.95
2021	56,131.27	4,470.59
2022	62,880.24	4,710.39
2023	70,419.23	4,962.99
2024	78,835.22	5,229.09
2025	88,223.30	5,509.39
2026	98,687.14	5,804.64
2027	110,339.21	6,115.63
2028	123,300.97	6,443.19
2029	137,702.83	6,788.19
2030	153,683.90	7,151.56
2031	171,391.35	7,534.26
2032	190,979.42	7,937.30
2033	212,607.91	8,361.75
2034	236,439.99	8,808.73
2035	262,639.32	9,279.42
2036	291,366.20	9,775.05
2037	322,772.68	10,296.92
2038	356,996.55	10,846.40
2039	394,153.93	11,424.91
2040	434,330.53	12,033.97
2041	477,571.44	12,675.15
2042	523,869.59	13,350.11
2043	573,153.04	14,060.58
2044	625,271.46	14,808.38
2045	679,982.25	15,595.43
2046	736,937.35	16,423.73
2047	795,671.37	17,295.36
2048	855,592.72	18,212.54
2049	915,978.95	19,177.56
2050	975,977.99	20,192.82

Though robust, the Bass model does have a few limitations. The Bass model does not account for changing market conditions, i.e., it fails to capture the diversity and heterogeneity of a real-world market system. The assumptions associated with applying the Bass model rely on the notion that all the entities or individuals within the considered system will adopt the product being analyzed. This shortcoming is particularly pertinent to the REE market which is evolving very quickly. For instance, the Dy content in REPMs is on the decline and while the overall demand for clean energy technologies and REPM consuming technologies is increasing, it is possible that lower Dy contents help stabilize the Dy requirement in the coming years. Other dynamics are at play as well. Given the monopolistic REE market, countries across the world are developing REE recovery and recycling capabilities to offset their dependence on primary REE feedstocks and reduce their dependence on Chinese exports. Furthermore, research to identify substitute materials is also underway to reduce our dependence on REEs. The Bass model fails to

capture these market uncertainties because it assumes every commodity is a success and the sales reach a steady state level.

On the other hand, the Bass model does provide a useful starting point in estimating a range for future Nd and Dy demands (Table 3). The fact that it is a parsimonious model that requires limited data in order to forecast sales growth is a clear advantage. The model could thus be beneficial in forecasting commodity diffusion patterns across shorter time periods for the REE market. As we continue to gain a better understanding of the clean energy technologies and REPM markets in the coming years, it is anticipated that access to more disaggregated data will become available. This in turn may help in making more accurate forecasts using the Bass model itself. Going forward, there also lies opportunity to explore more complex variations of the Bass Diffusion Model.

## 5. Summary and conclusion

This paper addresses the gap associated with limited market parameters around REEs. Given the limited data pertaining to future REPM demands, the Bass Diffusion Model was applied to estimate global Nd<sub>2</sub>O<sub>3</sub> and Dy<sub>2</sub>O<sub>3</sub> demands. Coefficients p and q were computed using the limited demand data points available in the literature. The model estimates Nd demand could be in the range of a million tons, while Dy demand could cross 20 thousand tons by 2050. Stoichiometric conversion factors were then applied to determine REE Nd and Dy demands. Understanding future Nd and Dy demand is just one component to enabling strategists and technologists working towards decarbonization in developing plans to address the uncertainty associated with the REE market, and by extension the clean energy technology market.

## Appendix A: Supporting data

Table A1: Nd<sub>2</sub>O<sub>3</sub> and Dy<sub>2</sub>O<sub>3</sub> demands in literature (2008 – 2030) [34, 35]

Year	Nd <sub>2</sub> O <sub>3</sub> (tons)	Dy <sub>2</sub> O <sub>3</sub> (tons)
2008	23,900	<i>data unavailable</i>
2009	15,300	2,255
2010	21,600	2,500
2011	18,900	2,745
2012	22,500	2,990
2013	23,400	3,235
2014	25,200	3,480
2015	36,217.11	3,725
2016	40,144.74	3,871
2017	44,072.37	4,017
2018	48,000.00	4,163
2019	51,927.63	4,309
2020	55,855.26	4,765
2021	66,240.79	4,997
2022	73,626.32	5,229
2023	82,511.84	5,461
2024	91,397.37	5,693
2025	10,0282.89	6,730
2026	11,5190.79	7,024
2027	13,0098.68	7,318
2028	14,5006.58	7,612



2029	15,9914.47	7,906
2030	17,4822.37	8,475

Table A2: REO to REE conversion factors [38]

REO	REE	Conversion factor
Nd <sub>2</sub> O <sub>3</sub>	Nd	0.857
Dy <sub>2</sub> O <sub>3</sub>	Dy	0.872

## References

- Watari, T., Nansai, K., & Nakajima, K. (2020). Review of critical metal dynamics to 2050 for 48 elements. *Resources, Conservation and Recycling*, 155(January), 104669. <https://doi.org/10.1016/j.resconrec.2019.104669>
- IPCC, 2023: Summary for Policymakers. In: Climate Change 2023: Synthesis Report. Contribution of Working Groups I, II and III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change [Core Writing Team, H. Lee and J. Romero (eds.)]. IPCC, Geneva, Switzerland, pp. 1-34, doi: 10.59327/IPCC/AR6-9789291691647.001
- USEPA (2021) Sources of Greenhouse Gas Emissions <https://www.epa.gov/ghgemissions> [Accessed September 2023]
- Mathur, Nehika (2021). Sustainability of Clean Energy Technologies via Industrial Ecology Computational Methods. Purdue University Graduate School. Thesis. <https://doi.org/10.25394/PGS.14657622.v1>
- Mancheri, N. A., Sprecher, B., Bailey, G., Ge, J., & Tukker, A. (2019). Effect of Chinese policies on rare earth supply chain resilience. *Resources, Conservation and Recycling*, 142(July 2018), 101–112. <https://doi.org/10.1016/j.resconrec.2018.11.017>
- Maani, T., Mathur, N., Rong, C., & Sutherland, J. W. (2023). Estimating potentially recoverable Nd from end-of-life (EoL) products to meet future US demands. *Resources, Conservation and Recycling*, 190, 106864. doi: 10.1016/j.resconrec.2023.106864
- IEA (2023) Global EV Data Explorer, IEA, Paris <https://www.iea.org/data-and-statistics/data-tools/global-ev-data-explorer> [Accessed September 2023]
- Constantinides, S. (2012, September). The demand for rare earth materials in permanent magnets. In *51st Annual Conference of Metallurgists* (Vol. 7546, p. 15).
- Schulze, R., & Buchert, M. (2016). Estimates of global REE recycling potentials from NdFeB magnet material. *Resources, Conservation and Recycling*, 113, 12-27. <https://doi.org/10.1016/j.resconrec.2016.05.004>
- Maani, T., Mathur, N., Singh, S., Rong, C., & Sutherland, J. W. (2021). Potential for Nd and Dy Recovery from end-of-life products to meet future electric vehicle demand in the US. *Procedia CIRP*, 98, 109-114. <https://doi.org/10.1016/j.procir.2021.01.014>
- Dushyantha, N., Batapola, N., Ilankoon, I. M. S. K., Rohitha, S., Premasiri, R., Abeyasinghe, B., Ratnayake, N. & Dissanayake, K. (2020). The story of rare earth elements (REEs): Occurrences, global distribution, genesis, geology, mineralogy and global production. *Ore Geology Reviews*, 122, 103521. <https://doi.org/10.1016/j.oregeorev.2020.103521>
- Zhou, B., Li, Z., Zhao, Y., Zhang, C., & Wei, Y. (2016). Rare Earth Elements supply vs. clean energy technologies: new problems to be solve. *Gospodarka Surowcami Mineralnymi*, 32(4), 29-44. doi: 10.1515/gospo-2016-0039
- Roskill. (2015). *Rare Earths: Market Outlook to 2020*. 2015. Roskill Information Services.
- Kingsnorth, D. 2013. Rare earths: Is Supply Critical in 2013? [Online] Available at: <http://investorintel.com/wp-content/uploads/2013/08/AusIMM-CMC-2013-DJK-Final-InvestorIntel.pdf> [Accessed September 2023].
- Alonso, E., Wallington, T., Sherman, A., Everson, M., Field, F., Roth, R., & Kirchain, R. (2012). An assessment of the rare earth element content of conventional and electric vehicles. *SAE International Journal of Materials and Manufacturing*, 5(2), 473-477, doi: 10.4271/2012-01-1061
- Rogers, E. M. (1987). The diffusion of innovations perspective. *Taking care: Understanding and encouraging self-protective behavior*, 79-94. Cambridge University Press <https://doi.org/10.1017/CBO9780511527760.006>
- Rao, K. U., & Kishore, V. V. N. (2010). A review of technology diffusion models with special reference to renewable energy technologies. *Renewable and sustainable energy reviews*, 14(3), 1070-1078. <https://doi.org/10.1016/j.rser.2009.11.007>
- Sudtasan, T., & Mitomo, H. (2017). Comparison of diffusion models for forecasting the growth of broadband markets in Thailand. <http://hdl.handle.net/10419/168541>
- Lartey, F. M. (2020). Predicting Product uptake using Bass, Gompertz, and Logistic diffusion models: Application to a broadband product. *Journal of Business Administration Research*. IX (2). <https://doi.org/10.5430/jbar.v9n2p5>
- Young, P., & Ord, J. K. (1989). Model selection and estimation for technological growth curves. *International journal of forecasting*, 5(4), 501-513. [https://doi.org/10.1016/0169-2070\(89\)90005-8](https://doi.org/10.1016/0169-2070(89)90005-8)
- Young, P. (1993). Technological growth curves: a competition of forecasting models. *Technological forecasting and social change*, 44(4), 375-389. [https://doi.org/10.1016/0040-1625\(93\)90042-6](https://doi.org/10.1016/0040-1625(93)90042-6)
- Meade, N., & Islam, T. (1995). Forecasting with growth curves: An empirical comparison. *International journal of forecasting*, 11(2), 199-215. [https://doi.org/10.1016/0169-2070\(94\)00556-R](https://doi.org/10.1016/0169-2070(94)00556-R)
- Park, S. Y., Kim, J. W., & Lee, D. H. (2011). Development of a market penetration forecasting model for Hydrogen Fuel Cell Vehicles considering infrastructure and cost reduction effects. *Energy Policy*, 39(6), 3307-3315, <https://doi.org/10.1016/j.enpol.2011.03.021>
- Da Silva, H. B., Uturbey, W., & Lopes, B. M. (2020). Market diffusion of household PV systems: Insights using the Bass model and solar water heaters market data. *Energy for Sustainable Development*, 55, 210-220, <https://doi.org/10.1016/j.esd.2020.02.004>
- Ismail, Z., & Abu, N. (2013). New car demand modeling and forecasting using bass diffusion model. *American Journal of Applied Sciences*, 10(6), 536-541. doi:10.3844/ajassp.2013.536.541
- Massiani, J., & Gohs, A. (2015). The choice of Bass model coefficients to forecast diffusion for innovative products: An empirical investigation for new automotive technologies. *Research in transportation economics*, 50, 17-28, <https://doi.org/10.1016/j.retrec.2015.06.003>
- Paschalia, D. G. (2012). The non-linear Bass diffusion model on Renewable Energy Technologies in European countries.
- Van den Bulte, C. (2002). Want to know how diffusion speed varies across countries and products? Try using a Bass model. *PDMA visions*, 26(4), 12-15.
- Parker, P. M. (1994). Aggregate diffusion forecasting models in marketing: A critical review. *International journal of forecasting*, 10(2), 353-380. [https://doi.org/10.1016/0169-2070\(94\)90013-2](https://doi.org/10.1016/0169-2070(94)90013-2)
- Bakher Naseri, M., & Elliott, G. (2013). The diffusion of online shopping in Australia: Comparing the Bass, Logistic and Gompertz growth models. *Journal of Marketing Analytics*, 1, 49-60. <https://doi.org/10.1057/jma.2013.2>
- Van den Bulte, Christophe, and Stefan Stremersch. "Social contagion and income heterogeneity in new product diffusion: A meta-analytic test." *Marketing Science* 23.4 (2004): 530-544. <https://doi.org/10.1287/mksc.1040.0054>
- Bass, F. M. (1969). A new product growth for model consumer durables. *Management science*, 15(5), 215-227. <https://doi.org/10.1287/mnsc.15.5.215>
- Rogers, E. M. (2003). Diffusion of Innovations fifth Ed Free Press. New York. *Rezvani, Z., Jansson, J. & Bodin*
- Hart, M. (2013). *Evaluating United States and world consumption of neodymium, dysprosium, terbium, and praseodymium in final products*. Colorado School of Mines.
- Hoenderdaal, S., Espinoza, L. T., Marscheider-Weidemann, F., & Graus, W. (2013). Can a dysprosium shortage threaten green energy technologies?. *Energy*, 49, 344-355.
- Li, X. Y., Ge, J. P., Chen, W. Q., & Wang, P. (2019). Scenarios of rare earth elements demand driven by automotive electrification in China: 2018–2030. *Resources, Conservation and Recycling*, 145, 322-331. <https://doi.org/10.1016/j.resconrec.2019.02.003>
- IEA, Global car sales by key markets, 2005-2020, IEA, Paris <https://www.iea.org/data-and-statistics/charts/global-car-sales-by-key-markets-2005-2020>, IEA. Licence: CC BY 4.0
- James Cook University, Australia (2016) Element-to-Stoichiometric Oxide Conversion Factors. <https://www.jcu.edu.au/advanced-analytical-centre/services-and-resources> [Accessed September 2023].