

Exploring Social Dynamics of Hard-Disk Drives Circularity with an Agent-Based Approach

Preprint

Julien Walzberg,¹ Kali Frost,² Fu Zhao,² Alberta Carpenter,¹ and Garvin A. Heath¹

1 National Renewable Energy Laboratory 2 Purdue University

Presented at the IEEE Conference on Technologies for Sustainability (SusTech 2021) April 22-24, 2021

NREL is a national laboratory of the U.S. Department of Energy Office of Energy Efficiency & Renewable Energy Operated by the Alliance for Sustainable Energy, LLC **Conference Paper** NREL/CP-6A20-79041 August 2021

This report is available at no cost from the National Renewable Energy Laboratory (NREL) at www.nrel.gov/publications.

Contract No. DE-AC36-08GO28308



Exploring Social Dynamics of Hard-Disk Drives Circularity with an Agent-Based Approach

Preprint

Julien Walzberg,¹ Kali Frost,² Fu Zhao,² Alberta Carpenter,¹ and Garvin A. Heath¹

Suggested Citation

Walzberg, Julien, Kali Frost, Fu Zhao, Alberta Carpenter, and Garvin A. Heath. 2021. Exploring Social Dynamics of Hard-Disk Drives Circularity with an Agent-Based Approach: Preprint. Golden, CO: National Renewable Energy Laboratory. NREL/CP-6A20-79041. https://www.nrel.gov/docs/fy21osti/79041.pdf.

© 2021 IEEE. Personal use of this material is permitted. Permission from IEEE must be obtained for all other uses, in any current or future media, including reprinting/republishing this material for advertising or promotional purposes, creating new collective works, for resale or redistribution to servers or lists, or reuse of any copyrighted component of this work in other works.

NREL is a national laboratory of the U.S. Department of Energy Office of Energy Efficiency & Renewable Energy Operated by the Alliance for Sustainable Energy, LLC Conference Paper NREL/CP-6A20-79041 August 2021

This report is available at no cost from the National Renewable Energy Laboratory (NREL) at www.nrel.gov/publications.

Contract No. DE-AC36-08GO28308

National Renewable Energy Laboratory 15013 Denver West Parkway Golden, CO 80401 303-275-3000 • www.nrel.gov

NOTICE

This work was authored in part by the National Renewable Energy Laboratory, operated by Alliance for Sustainable Energy, LLC, for the U.S. Department of Energy (DOE) under Contract No. DE-AC36-08GO28308. Funding provided by the U.S. Department of Energy Office of Energy Efficiency and Renewable Energy Advanced Manufacturing Office and the Office of Strategic Programs. The views expressed herein do not necessarily represent the views of the DOE or the U.S. Government. The U.S. Government retains and the publisher, by accepting the article for publication, acknowledges that the U.S. Government retains a nonexclusive, paid-up, irrevocable, worldwide license to publish or reproduce the published form of this work, or allow others to do so, for U.S. Government purposes.

This report is available at no cost from the National Renewable Energy Laboratory (NREL) at <u>www.nrel.gov/publications</u>.

U.S. Department of Energy (DOE) reports produced after 1991 and a growing number of pre-1991 documents are available free via www.OSTI.gov.

Cover Photos by Dennis Schroeder: (clockwise, left to right) NREL 51934, NREL 45897, NREL 42160, NREL 45891, NREL 48097, NREL 46526.

NREL prints on paper that contains recycled content.

Exploring Social Dynamics of Hard-Disk Drives Circularity with an Agent-Based Approach

Julien Walzberg National Renewable Energy Laboratory Golden, United States of America Julien.Walzberg@nrel.gov

Kali Frost Division of Environmental and Ecological Engineering Purdue University West Lafayette, United States of America Fu Zhao

Division of Environmental and Ecological Engineering Purdue University West Lafayette, United States of America

> Alberta Carpenter National Renewable Energy Laboratory Golden, United States of America

Garvin A. Heath National Renewable Energy Laboratory Golden, United States of America

Abstract-By 2025, it is estimated that installed data storage in the U.S. will be 2.2 Zettabytes, generating about 50 million units of end-of-life hard-disk drives (HDDs) per year. The circular economy (CE) tackles waste issues by maximizing value retention in the economy, for instance, through reuse and recycling. However, the reuse of hard disk drives is hindered by the lack of trust organizations have toward other means of data removal than physically destroying HDDs. Here, an agent-based approach explores how organizations' decisions to adopt other data removal means affect HDDs' circularity. The model applies the theory of planned behavior to model the decisions of HDDs endusers. Results demonstrate that the attitude (which is affected by trust) of end-users toward data-wiping technologies acts as a barrier to reuse. Moreover, social pressure can play a significant role as organizations that adopt CE behaviors can set an example for others.

Keywords—Circular economy; agent-based modeling; theory of planned behavior; socio-technical systems; hard-disk drives

I. INTRODUCTION

Between 2010 and 2018, the global data center storage capacity has grown by 25-fold and is expected to keep increasing [1]. In the United States (U.S.) only, the installed storage capacity is expected to increase from 1.5 to 4.7 Zettabytes between 2018 and 2025 [2]. Aside from energy requirements – data centers already represent 1% of worldwide electricity use [1] – storage technologies require critical minerals such as barite (used to produce barium ferrite in tape drives), neodymium and dysprosium (used in hard disk drives (HDDs)), and silicon (used in solid-state drives (SSDs)) [3]. As the demand for storage increases, it will strain further the limited supplies of critical materials and, thus, intensify the potential risk posed by sudden supply restrictions to the economy. The circular economy (C.E.) could solve the

challenge of the increasing demand for critical materials by circulating resources within the economy, thereby minimizing end-of-life (EOL) waste.

The C.E. is accomplished by encouraging the reduction and reuse of products and materials, thus, decoupling economic growth from resource depletion [4]. Although SSDs are expected to represent a larger share of the U.S. storage capacity, HDDs will still be the significant storage technology in the near-medium terms [2]. Factors in favor of applying C.E. principles to manage HDDs EOL in the U.S. are standardized sizes (2.5" or 3.5"), a high collection rate, and current reliability on imported rare-earth elements (REE) such as neodymium and dysprosium [5]. Overall, improving HDDs circularity could reduce environmental impacts associated with mining and processing of REE [5], as well as lessen the risk posed by supply restrictions for the economy [6].

Challenges to improved HDDs circularity are multiple. First, regarding recycling, REE are rarely recovered as it isn't a widespread practice. When REE are indeed recovered, the instability of REE prices and their low concentrations in EOL materials may hinder recycling profitability [6]. Next, component reuse, such as rare earth magnet and magnet assembly (or voice coil motor assembly) reuse, faces logistic (due to the lack of downstream processing facilities in the U.S.) and lock-in (due to the high maturity of the industry) issues [5, 6]. Finally, reuse is inhibited by the perceived data security risks and lack of trust in data-wiping technologies [6]. HDD end-users often require physical destruction of HDDs through shredding, even when standardized (e.g., following NIST 800-88 R1 standard) and complete data-wiping is possible. This fact has led to widespread HDD shredding rather than reuse, an EOL option, which besides being the least circular, is also the worst on an environmental and value-recovery point-of-view [5].

Although the HDD industry stakeholders are aware of those challenges, even HDDs that do not require a high-security level are sent to the shredder, effectively removing any other EOL options such as component or HDD reuse [6]. Several surveys found that the lack of trust in data wiping technology is one of the main barriers to reusing information and communication technology equipment [6, 7]. Whalen et al. [7], for instance, surveyed two Swedish companies and found that, despite significant investments to create an efficient and secure data wiping process by one of the companies, data security concerns remain one of the most critical barriers to overcome.

Trust – understood as a state of perceived vulnerability stemming from the uncertainty an individual (or organization) has regarding the motives and intentions of others on whom they depend [8] – therefore affects end-users' decisions to choose an EOL option that does not involve shredding. Among many social psychology theories aiming to explain and model human decision processes, the theory of planned behavior (TPB) is prevalent [9]. The use of the TPB to explain proenvironmental and circular behaviors in industrial ecology publications has been growing [10]. Trust was found to be an antecedent of TPB's factors, especially regarding attitude [8]. Therefore, the TPB can model the lack of trust that HDD end users have regarding data wiping technologies and provide a causal mechanism for their adoption.

While traditional industrial ecology frameworks such as life cycle sustainability assessment (LCSA) and environmentally extended input-output analysis can quantitatively assess the sustainability of C.E. strategies, such tools usually do not model the dynamic changes implied by the C.E. transition, such as new technology or behavior adoption [11, 12]. On the contrary, agent-based modeling (ABM) is a framework that is well suited for studying the C.E. transition because it dynamically accounts for behavioral change and, thus, can complement industrial ecology frameworks [11]. In agentbased modeling (ABM), a system is represented through agents, representing various system elements such as organizations, individuals, or households depending on the system. A strength of ABM is its ability to provide a detailed representation of the agents' decision processes [11].

ABM often employs social psychology theories such as TPB to represent human decisions and, thus, can more adequately model socio-technical systems [11]. ABM has been applied in C.E., mainly to study industrial symbiosis and waste management [11]. For example, an ABM on electronic waste studied the consumers' adoption of four EOL pathways for used electronics: storage, shredding, sale, and return through a product take-back system [13]. While the model is not based on empirical data (i.e., data collected in the real world) it includes relevant features affecting the take-back system's adoption, such as consumers' data security concerns. This paper aims to apply an ABM approach to study how social factors, such as lacking trust in data wiping technologies, affect HDD circularity.

A few ABM have been used to explore electronic waste management [13, 14], but they have not applied empirical data,

limiting their application. Moreover, they focused on residential rather than organizational end-users and did not include other C.E. stakeholders, such as recyclers and initial service providers. The ABM presented here fills those gaps by including four types of HDD industry stakeholders, using empirical data whenever possible, and calibrating the model to known outputs.

II. MATERIALS AND METHODS

The ABM from previous work on photovoltaics (P.V.) circularity is adapted for this study [15]. While the model's general structure is the same, values for the parameters were changed to correspond to the HDD industry. Moreover, some parameters were modified (e.g., the repair option considered in the P.V. model was replaced by a component reuse option). The overview, design concepts, and details (ODD) protocol [16] is used to describe the ABM.

A. Overview and design concepts

In short, the ABM considers four of the main stakeholders of the HDD industry: end-users, recyclers, initial service providers (with some companies having both roles), and manufacturers (Figure 1-a). End-users include service providers, governmental entities, and commercial customers. Manufacturers include original equipment manufacturers (OEM) and other manufacturers such as aluminum smelters (to account for both closed and open-loop recycling). Five EOL options are modeled: HDD reuse, component reuse, recycling with REE recovery, shredding, and storage. After shredding, materials are either recycled (without REE recovery, which is the current practice) or landfilled. The model's objective is to explore what technical, economic, and social factors maximize HDD circularity. Thus, the primary output of the ABM is the mass volumes of HDDs and HDD materials reaching each EOL option.

The ABM is designed in a modular fashion where each agent type is a class defined in a Python module. Thus, each agent is an instance of the class of its type. Another Python module contains the model inputs, activates the agents, and collects the simulation outputs. The Mesa Python package facilitates the agents' activation and sets up batch runs of simulations [17]. There are several interactions between the agents in the model. First, within agents of the same type to model the effect of peer influence on agents' decisions and second between agents of different types. For instance, initial service providers have access to the number of HDDs handed over by end-users for reuse, component reuse, and recycling. The model also contains several stochastic elements (i.e., it uses the stochastic Watts Strogatz algorithm to build the endusers social network, and some of the agents' characteristics are drawn from probability distributions to model their variability (e.g., recycling costs may be different across the U.S.)). During the simulation, individual agents' decisions and interactions are responsible for the HDD industry's overall circularity modeled in the ABM.

B. Details

The installed capacity of HDDs from 2000 to 2020 is reported in the ABM and divided among end-user agents [18, 19]. Due to computational limitations, the number of end-users is restricted to 1,000 agents, assumed to represent HDD endusers' whole population. Although it limits the ABM's representativeness, this number was found to capture network effects and end-users' variability. The number of recycler, initial service provider, and manufacturer agents are 250, 15, and 13 (including the 3 OEMs), respectively [6, 20, 21].

Product growth is modeled with the compound annual growth rate formula, using a growth rate derived from Gantz et al. [2] projections. The HDDs' material efficiency growth (i.e., the increase of storage capacity per unit of mass) is derived from Fontana Jr and Decad [22], although the fractions of the different materials in the HDDs are assumed to remain the same [23]. Next, a Weibull function is used to generate the number of HDDs W_i^i of agent *i* reaching EOL at time *t*.

The TPB is used to model end-users purchase of used or new HDDs and the EOL management decisions (Figure 1-b). The TPB accounts for three main factors affecting the intention to perform a behavior *j*, BI_{ij} ^t: 1) the perceived behavioral control (PBC) PBC_{ij} ^t, which relates to the perceived ease or difficulty of performing the behavior (assumed to only relate to the financial costs of performing the behavior in this ABM), 2) the attitude A_{ij} ^t held toward the behavior (i.e., how the behavior is perceived as favorable or unfavorable), and 3) the subjective norms SN_{ij} ^t, which refers to the perceived social pressure to perform or not perform the behavior (Equation 1). The regression coefficients weight the model variables (w_{PBC} , w_A , and w_{SN} , taken from meta-analyses on EOL and second-hand purchase behaviors [24, 25]).

$$BI_{ij}^{t} = w_{PBC}PBC_{ij}^{t} + w_{A}A_{ij}^{t} + w_{SN}SN_{ij}^{t}$$
^[1]

While A_{ij}^{i} is unknown and therefore calibrated, PBC_{ij}^{i} is computed from the costs of each EOL option [6, 26], and SN_{ij}^{i} is computed as a function of the number of agent *i* neighbors that have adopted behavior *j* in the social network relating endusers. Each agent *i* then selects the EOL or purchase option *j* with the highest score BI_{ij}^{i} at each *t* (i.e., one year). The number of HDDs W_i^{t} is then added to the tally of the option chosen by agent *i*, providing an account of the mass volumes of HDDs and HDD materials reaching each EOL option over time.

Initial service provider agents sort HDDs from end-users that are not shredded between the three circular options (reuse, component reuse, and recycling with REE recovery) depending on their technical feasibility and value proposition. It is assumed from discussion with industry stakeholders during the iNEMI project that 60% of HDDs can be reused (i.e., they are still functioning), and 95% of the magnets can be recovered intact (if removed within a clean room environment under strict process controls) [6, 27]. Moreover, value recovery for the reuse, magnet reuse (i.e., component reuse), and recycling are \$15-23/TB, \$0.5-3.3/TB, and \$0.4/TB respectively [6]. The processing and labor costs are also considered when the initial service providers sort EOL HDDs [6, 26-30]. Initial service providers also balance end-users supply and demand of used HDDs. If there is insufficient demand for used HDDs

(determined by the end-users purchase decision) or if HDDs cannot be reused (i.e., if already 60% of EOL HDDs are reused), they are sent to another EOL option.

Recycler agents compute the volume of recovered materials from EOL HDDs according to the HDDs mass fraction [23] and the recycling process's material recovery rates [28, 31]. Manufacturer agents purchase recovered materials from recyclers – at scrap prices if they exist (e.g., the price of aluminum scrap is often about 60% of the price of virgin aluminum [32]) and at virgin prices otherwise. Finally, 30 simulations spanning the 2020-2050 period are run for each scenario explored with the ABM, as this number of replicates proved to be enough to capture the model's stochasticity in a stability analysis [15].



Figure 1. a) Overview of the HDDs ABM; b) HDDs end users decision tree

III. RESULTS

Although empirical data are limited, the model was calibrated to best represent the current situation. The baseline scenario yields a low circularity rate and is mainly limited by end-users' unwillingness to trust data-wiping technologies. After data wiping, the initial service providers sell the end users' used HDDs, their components or perform advanced recycling. As a validation of the general behavior of the ABM, the projected growth of installed capacity (about 2 zettabytes in 2025), the amount of waste generated (around 20 to 70 million HDDs per year), and low reuse rate (about 6%) were found similar to data published in the literature [2, 27, 33, 34]. The lack of data on the reuse rate prevents a more thorough validation.

In addition to comparing simulation results with the literature, extreme cases were tested to ensure that the model behaved as expected (Table 1). In the baseline scenario (Table 1 scenario a), most HDD materials are already recycled. Indeed, given the current shredding practices, the steel, copper, and aluminum that constitute most HDD's mass are recovered [31]. Next, the reuse rate depends on the end-users' willingness to use data-wiping technologies but also on the failure rate and the demand for used HDDs (Table 1 scenarios b and d). By contrast, if the aforementioned constraints affecting reuse are lifted, the reuse rate increases to 70% (Table 1 scenario e). Due to HDDs' short life cycle and the number of reuses assumed to be limited to two, there are still 20% and 7% of materials that end up being recycled and landfilled, respectively, in that scenario. Finally, when removing the circular options from the list of choices available to the agents, all HDDs are shredded, leading to 73% of the materials being recycled and 27% being landfilled or stored. It is worth noting that storage behaviors were observed in residential and organizational end-users [35] and may act as a buffer that leaves room for other EOL options to be chosen in subsequent time-steps [15]. Figure 2 shows the fraction of HDDs in circular EOL pathways in 2050 as a function of the trust end-users have against data wiping technologies for various scenarios.

First, circularity never reaches 100% because government end users always choose to shred their HDDs (according to current policies), and reuse is assumed to be limited to two lifecycles. Then, the effect of the TPB's variables can be observed from Figure 2. For instance, comparing the red (and brown) and blue curves in Figure 2 shows that the variable accounting for subjective norms acts as a double-edged sword: it reinforces the lack of trust toward data mining technologies when trust is already low among agents but also enhances that trust once it has been established (when the agents' attitude is already high). Moreover, because HDDs that are sold for reuse can bring financial benefits to the end-users (it is the EOL pathway capturing the highest value), the PBC lowers the attitude threshold necessary for reusing magnet material (see blue and green curves in Figure 2). When the decision is based only on the PBC, the magnet materials' circularity rate is maximal (orange curve in Figure 2). When only peer influence (i.e., subjective norms) is accounted for in the model, the magnet materials' circularity is 0% as at the beginning of the simulation, and most agents are not willing to trust data-wiping and influence all other agents to do the same (pink curve in Figure 2). On the contrary, if the effect of attitude on the endusers' decision is lifted, the magnet materials' circularity rate is almost maximal (the subjective norm still hinders circularity at the beginning of the simulations) (purple curve in Figure 2). When all TPB's factors are lifted, end-users randomly choose between shredding (about 35% of agents' decisions), handling their HDDs to the initial providers (about 35% of agents' decisions), and storing HDDs (about 30% of agents' decisions) (grey curve in Figure 2). Storing is selected less often as it is a temporary solution and therefore assumed not to be chosen twice in a row by the agents. Those mechanisms result in a magnet circularity rate of about half the possible maximum.



Figure 2. Effect of TPB's parameters (A=attitude, SN=subjective norms, PBC=perceived behavioral control) on magnet material circularity (HDD reuse, magnet reuse, REE recycling)

 TABLE I.
 FRACTIONS OF MATERIALS IN END-OF-LIFE PATHWAYS AT THE END OF THE SIMULATION PERIOD (2050) ACCORDING TO DIFFERENT SCENARIOS (MEAN OF 30 REPLICATES FOR EACH SCENARIO).

	% Reuse	% Magnet reuse	% Recycle	% Landfill	% Storage
a) Baseline	6	1	68	24	<1
b) 0% HDD repairability	0	7	68	24	<1
c) CE pathways unavailable	0	0	73	26	<1
d) No demand for used HDD	0	8	68	24	0
e) Ideal reuse case	70	3	20	7	0

IV. CONCLUSION

The ABM presented in this paper develops similar work from the literature [13, 14] by applying empirical data and a calibration procedure. By basing agents' EOL management and second-hand purchase decisions on the TPB, the model enables exploring social dynamics of circularity in the HDD industry. For instance, only once the trust of end-users in data-wiping technologies is high enough that circular options are adopted in the model. Similarly, the subjective norms play an essential role as they may hinder or enhance the adoption of circular options in the end-user social network.

Overall, the reuse rate is primarily constrained by endusers' unwillingness to adopt other EOL options than shredding for data security reasons. Furthermore, an exciting research avenue would be to study several technology adoptions at once, for instance, to capture the increase in renewable energy use by data centers [36].

There are several limitations to the ABM presented herein. First, competition between agents is not accounted for. Initial service providers, for instance, could compete to access endusers with the highest volume of EOL HDDs. Next, households were excluded from the analysis, although they also contribute to the generation of electronic waste and, thus, HDDs. However, households represent a small share of the total installed HDD capacity (below 10%) [18, 19]. More limitations include the exclusion of environmental metrics in the analysis and considerations of international logistics (e.g., regarding the shipment of small quantities of REE to Asia as there are no facilities in the U.S. that can use recovered REE).

Research opportunities include combining the current model with a more macroscopic framework such as system dynamics, for instance, to capture international flows. Moreover, a scenario including SSDs could also be explored with the ABM.

ACKNOWLEDGMENT

This work was authored in part by the National Renewable Energy Laboratory, operated by Alliance for Sustainable Energy, LLC, for the U.S. Department of Energy (DOE) under Contract No. DE-AC36-08GO28308. Funding provided by the Advanced Manufacturing Office and the Office of Strategic Programs. The views expressed in the article do not necessarily represent the views of the DOE or the U.S. Government. The U.S. Government retains and the publisher, by accepting the article for publication, acknowledges that the U.S. Government retains a nonexclusive, paid-up, irrevocable, worldwide license to publish or reproduce the published form of this work, or allow others to do so, for U.S. Government purposes. We would also like to thank Robin Burton and Liam Watts for their help with data collection.

REFERENCES

 E. Masanet, A. Shehabi, N. Lei, S. Smith, and J. Koomey, "Recalibrating global data center energy-use estimates," Science, vol. 367, no. 6481, pp. 984-986, 2020, doi: 10.1126/science.aba3758.

[2] J. F. Gantz, D. Reinsel, and J. Rydning. "The U.S. Datasphere: Consumers Flocking to Cloud." https://www.seagate.com/files/wwwcontent/our-story/trends/files/data-age-us-idc.pdf (accessed 12/31/2020, 2020).

[3] European Commission. "Communication from the commission to the european parliament, the council, the european economic and social committee and the committee of the regions on the 2017 list of critical raw materials for the E.U." https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:52017DC0490&from=en (accessed 12/31/2020, 2020).

[4] M. Linder, S. Sarasini, and P. van Loon, "A Metric for Quantifying Product-Level Circularity," Journal of Industrial Ecology, vol. 21, no. 3, pp. 545-558, 2017, doi: 10.1111/jiec.12552.

[5] H. Jin et al., "Life cycle assessment of emerging technologies on value recovery from hard disk drives," Resources, Conservation and Recycling, vol. 157, p. 104781, 2020/06/01/ 2020, doi: https://doi.org/10.1016/j.resconrec.2020.104781.

[6] iNEMI, "Value Recovery Project, Phase 2," 2019. [Online]. Available: https://community.inemi.org/value recovery 2

[7] K. A. Whalen, L. Milios, and J. Nussholz, "Bridging the gap: Barriers and potential for scaling reuse practices in the Swedish ICT sector," Resources, Conservation and Recycling, vol. 135, pp. 123-131, 2018/08/01/ 2018, doi: https://doi.org/10.1016/j.resconrec.2017.07.029.

[8] L. Canova, A. Bobbio, and A. M. Manganelli, "Buying Organic Food Products: The Role of Trust in the Theory of Planned Behavior," (in English), Frontiers in Psychology, Original Research vol. 11, no. 2611, 2020-October-23 2020, doi: 10.3389/fpsyg.2020.575820.

[9] O. Khan, T. Daddi, H. Slabbinck, K. Kleinhans, D. Vazquez-Brust, and S. De Meester, "Assessing the determinants of intentions and behaviors of organizations towards a circular economy for plastics," Resources, Conservation and Recycling, vol. 163, p. 105069, 2020/12/01/ 2020, doi: https://doi.org/10.1016/j.resconrec.2020.105069.

[10] A. Yuriev, M. Dahmen, P. Paillé, O. Boiral, and L. Guillaumie, "Pro-environmental behaviors through the lens of the theory of planned behavior: A scoping review," Resources, Conservation and Recycling, vol. 155, p. 104660, 2020/04/01/ 2020, doi: https://doi.org/10.1016/j.resconrec.2019.104660.

[11] J. Walzberg, G. Lonca, R. J. Hanes, A. L. Eberle, A. Carpenter, and G. A. Heath, "Do We Need a New Sustainability Assessment Method for the Circular Economy? A Critical Literature Review," (in English), Frontiers in Sustainability, Review vol. 1, no. 12, 2021-January-07 2021, doi: 10.3389/frsus.2020.620047.

[12] G. Moraga et al., "Circular economy indicators: What do they measure?," Resources, Conservation and Recycling, vol. 146, pp. 452-461, 2019/07/01/ 2019, doi: https://doi.org/10.1016/j.resconrec.2019.03.045.

[13] A. R. Mashhadi, B. Esmaeilian, and S. Behdad, "Simulation Modeling of Consumers' Participation in Product Take-Back Systems," Journal of Mechanical Design, vol. 138, no. 5, 2016, doi: 10.1115/1.4032773.

[14] A. R. Mashhadi, S. Behdad, and J. Zhuang, "Agent Based Simulation Optimization of Waste Electrical and Electronics Equipment Recovery," Journal of Manufacturing Science and Engineering, Transactions of the ASME, Article vol. 138, no. 10, 2016, Art no. 101007, doi: 10.1115/1.4034159.

[15] Walzberg, J., Carpenter, A., Heath, G., "Integrating sociotechnical factors to assess efficacy of PV recycling and reuse interventions." Nature Energy. In review, 10.21203/rs.3.rs-151153/v1

[16] V. Grimm et al., "A standard protocol for describing individualbased and agent-based models," Ecological Modelling, vol. 198, no. 1–2, pp. 115-126, 9/15/ 2006, doi: http://dx.doi.org/10.1016/j.ecolmodel.2006.04.023.

[17] D. Masad and J. Kazil, "MESA: an agent-based modeling framework," in 14th PYTHON in Science Conference, 2015, pp. 53-60.

[18] Y. Yang and E. Williams, "Logistic model-based forecast of sales and generation of obsolete computers in the U.S," Technological Forecasting and Social Change, vol. 76, no. 8, pp. 1105-1114, 2009/10/01/ 2009, doi: https://doi.org/10.1016/j.techfore.2009.03.004.

[19] A. Shehabi et al., "United States Data Center Energy Usage Report,"; Lawrence Berkeley National Lab. (LBNL), Berkeley, CA (United States), LBNL-1005775; Other: ir:1005775 United States 10.2172/1372902 Other: ir:1005775 LBNL English, 2016. [Online]. Available: https://www.osti.gov/servlets/purl/1372902

[20] EPA. "Certified Electronics Recyclers."

https://www.epa.gov/smm-electronics/certified-electronics-recyclers (accessed 08/19/20, 2020).

[21] Enterprise management 360. "Big server vendors losing market share to smaller, 'white box' suppliers." https://www.em360tech.com/tech-news/big-server-vendors-losing-market-share-smaller-white-box-suppliers/ (accessed 07/29/2020, 2020).

[22] R. E. Fontana Jr and G. M. Decad, "Moore's law realities for recording systems and memory storage components: HDD, tape, NAND, and optical," AIP Advances, vol. 8, no. 5, p. 056506, 2018.

[23] P. Tecchio, F. Ardente, M. Marwede, C. Clemm, G. Dimitrova, and F. Mathieux, "Analysis of material efficiency aspects of personal computers product group," Luxembourgh. doi, vol. 10, p. 89220, 2018.

[24] D. Singhal, S. K. Jena, and S. Tripathy, "Factors influencing the purchase intention of consumers towards remanufactured products: a systematic review and meta-analysis," International Journal of Production Research, vol. 57, no. 23, pp. 7289-7299, 2019/12/02 2019, doi: 10.1080/00207543.2019.1598590.

[25] J. L. Geiger, L. Steg, E. van der Werff, and A. B. Ünal, "A metaanalysis of factors related to recycling," Journal of Environmental Psychology, vol. 64, pp. 78-97, 2019/08/01/ 2019, doi: https://doi.org/10.1016/j.jenvp.2019.05.004.

[26] B. Ott, "Experimental methods of flowsheet development for hard drive recycling by preferential degradation and physical separation," Colorado School of Mines. Arthur Lakes Library, 2018.

[27] iNEMI, "Value Recovery from Used Electronics," 2017. [Online]. Available: https://community.inemi.org/value_recovery_2

[28] R. T. Nguyen, L. A. Diaz, D. D. Imholte, and T. E. Lister, "Economic assessment for recycling critical metals from hard disk drives using a comprehensive recovery process," JOM. Journal of the Minerals, Metals & Materials Society, p. Medium: E.D.; Size: 14 p., 2017. [Online]. Available: https://www.osti.gov/servlets/purl/1363744.

[29] U.S. Bureau of Labor Statistics. "Occupational employment statistics 2020." https://www.bls.gov/oes/home.htm (accessed 01/06/2021, 2020).

[30] L. T. Peiró, G. V. Méndez, and R. U. Ayres, "Material Flow Analysis of Scarce Metals: Sources, Functions, End-Uses and Aspects for Future Supply," Environmental Science & Technology, vol. 47, no. 6, pp. 2939-2947, 2013/03/19 2013, doi: 10.1021/es301519c.

[31] K. Habib, K. Parajuly, and H. Wenzel, "Tracking the Flow of Resources in Electronic Waste - The Case of End-of-Life Computer Hard Disk Drives," Environmental Science & Technology, vol. 49, no. 20, pp. 12441-12449, 2015/10/20 2015, doi: 10.1021/acs.est.5b02264.

[32] USGS, "2017 Minerals Yearbook - Aluminum," 2020. [Online]. Available: https://prd-wret.s3-us-west-2.amazonaws.com/assets/palladium/production/s3fs-public/atoms/files/mcs-

2.amazonaws.com/assets/panadrum/production/s51s-public/atoms/files/mcs-2019-alumi.pdf

[33] M. Sabbaghi, W. Cade, W. Olson, and S. Behdad, "The Global Flow of Hard Disk Drives: Quantifying the Concept of Value Leakage in Ewaste Recovery Systems," Journal of Industrial Ecology, vol. 23, no. 3, pp. 560-573, 2019, doi: 10.1111/jiec.12765.

[34] Google, "Environmental Report," 2019. [Online]. Available: https://sustainability.google/reports/

[35] M. Sabbaghi, B. Esmaeilian, A. Raihanian Mashhadi, S. Behdad, and W. Cade, "An investigation of used electronics return flows: A datadriven approach to capture and predict consumers storage and utilization behavior," Waste Management, vol. 36, pp. 305-315, 2015/02/01/ 2015, doi: https://doi.org/10.1016/j.wasman.2014.11.024.

[36] S&P Global. "The Growing Importance of Data Centersfor Europe & U.S. Renewable Projects."

https://pages.marketintelligence.spglobal.com/rs/565-BDO-100/images/european-and-us-data-center-infographic.pdf (accessed 01/07/2021, 2021).