The future of e-waste; which category is going to be the major challenge for the EU.

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ABSTRACT,
E-waste or also called WEEE is discarded electrical and electronic equipment (EEE). Right now, the waste management of e-waste is not good enough, only 17.4% of the world's total amount of e-waste is properly collected and recycled. This causes damage to the environment, to humans and makes that economic opportunities from the raw materials in e-waste are not used. Because e-waste is also one of the quickest growing waste streams, it is going to give big challenges to the EU. Given that the EU has been attempting for the past two decades to develop a circular economy, this paper researched which category of e-waste is going to be the major challenge for the EU. An Autoregressive Integrated Moving Average (ARIMA) model and an Artificial Neural Network (ANN) model were created to predict the future amounts of e-waste per category. This combined with the existing knowledge of recyclability, profitability and how good recycling facilities follow the EU directives about e-waste per category of e-waste, shows that the category of small equipment e-waste will be the major challenge for the EU.

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E-waste, ARIMA model, neural network, time series, forecasting, recycling, circular economy

1. INTRODUCTION

Electrical and electronic equipment (EEE) has become an important part of daily life. Rapid advancements in material science, manufacturing processes and electronic products have created global markets with rapid diffusion of technology to consumers (Tansel, 2017). This rapid diffusion has caused that waste electrical and electronical equipment (WEEE) or also called e-waste is now one of the fastest-growing waste streams (Widmer, Oswald-Krapf, Sinha-Khetriwal, Schnellmann, & Böni, 2005). Four key global issues that make WEEE a priority waste stream are:

1. Global quantities of WEEE
2. Resource impact
3. Potential health and environmental impacts
4. Ethical concerns

(Ongondo & Williams, 2011)

Challenges faced by WEEE management are not only consequences of growing quantities of waste but also the complexity of WEEE; it is one of the most complex waste streams because of the wide variety of products from mechanical devices to highly integrated systems and the accelerating technological innovations (Ylä-Mella, Pongrácz, & Keiski, 2004). Elements used in computers and high-tech devices that cause the WEEE add up to 49 different metals, including copper, gold, silver, palladium and platinum (Tansel, 2017). To some extent, the recovery of these metals from e-waste could reduce the global demand for new metal production. The recycling of e-waste will also help reduce the number of toxic chemicals that end up in landfills. In 2019 only 17.4% of the world's total amount of e-waste was properly collected and recycled (Forti, Baldé, Kuehr, & Bel, 2020).

The first section of this paper gives an understanding of e-waste and the categories of e-waste. The second section will give information about waste management, recycling and the impact of e-waste. After this, it will be connected to the categories of e-waste to give an overview including the differences between them. Then the EU legislation about e-waste will be explained, to show what is done about it right now. The third section is the methodology which gives information about the forecasting models used and how the data was collected and adapted. The fourth section is about the analysis, results and discussion of the time series forecast and, in the end, there is a conclusion about this. The research question of this paper is to find out which category of e-waste is going to be the major challenge for the EU.

1.1 Definition

Electrical and electronic equipment (EEE) is defined by the European Union (Directive 2012/19/EU) as: ''. . . equipment which is dependent on electrical currents or electromagnetic fields in order to work properly and equipment for the generation, transfer and measurement of such currents and fields and designed for use with a voltage rating not exceeding 1000 Volts for alternating current (AC) and 1500 Volts for direct current" (European Union, 2012). Shittu, Williams, and Shaw (2021) say that "EEE is often designed to function for a period, after which it ceases to function (end-of-life) or performs sub-optimally (obsolescence). When this occurs, the user or owner of the device may choose to discard it; when an item is discarded, it becomes waste EEE (WEEE or e-waste)". WEEE is also a term used to describe EEE and its subcomponents that have been, or intended to be, discarded by its owner with no intention of reuse (European Union, 2012).
In this paper, the term "CENELEC standards", refers generally to the series of European standards for the treatment of WEEE (EN 50625 series - collection, logistics & treatment requirements for WEEE) and the European standard on the requirements for the preparing for re-use of WEEE (EN 50614 - Requirements for the preparing for re-use of WEEE) (European Commission et al., 2021).

1.2 Categories of e-waste

The European Union (EU) has made a directive about waste from electrical and electronical equipment (WEEE), in this directive, they divided e-waste in two different ways. In the transitional period from 13 August 2012 to 14 August 2018, e-waste was divided into the following categories: 1. Large household appliances 2. Small household appliances 3. IT and telecommunications equipment 4. Consumer equipment and photovoltaic panels 5. Lighting equipment 6. Electrical and electronic tools (except for large-scale stationary industrial tools) 7. Toys, leisure and sports equipment 8. Medical devices (except for all implanted and infected products) 9. Monitoring and control instruments 10. Automatic dispensers. (European Union, 2012)
Since 15 Augustus 2018 the EU uses the following 6 categories:

1.2.1 Temperature exchange equipment

Temperature exchange equipment or as often called cooling and freezing equipment includes equipment like refrigerators, freezers, air conditioners and heat pumps. Aspects of this category that are relevant regarding environmental and health impacts are for example; oil in the cooling circuits of refrigerators and heaters and mercury-containing components in very old appliances (European Commission et al., 2021).

1.2.2 Screens, monitors, and equipment containing screens having a surface greater than 100 cm²

Examples of equipment that are included: are televisions, monitors, laptops, notebooks and tablets. In this category, you can see how a change in production technology can influence the amount of kg WEEE. The change comes from flat displays substituting CRT displays and monitors. The recycling process of CRT displays and monitors is luckily well-known and economically sustainable (P. Chancerel, Deubzer, Nissen, & Lang, 2012).

1.2.3 Lamps

Examples of equipment that are included are: fluorescent lamps, high-intensity discharge lamps and LED lamps. Mercury-containing gas discharge lamps, which were estimated to be 84% of lamps put on the market in 2012, are the main impact of setting minimum treatment requirements for lamps (Commission & Environment, 2014).

1.2.4 Large equipment

Examples of equipment that are included are: washing machines, clothes, dishwashing machines, electric stoves, large printing machines, copying equipment and photovoltaic panels. In the research conducted photovoltaic panels will have a separate category. Because of the bigger variety in large equipment, it is less common to use CENELEC standards for collection, transport and treatment. (European Commission et al., 2021). In practice, this means that the minimum standards for the treatment of WEEE set by the EU are not attained.

1.2.5 Small equipment

Examples of equipment that are included are: vacuum cleaners, microwaves, ventilation equipment, toasters, electric kettles, electric shavers, scales and calculators. Because of the bigger variety in this category, it is less common to use CENELEC standards for the collection, transport and treatment of small equipment (European Commission et al., 2021).

1.2.6 Small IT and telecommunication equipment

Examples of equipment that are included are: mobile phones, GPS devices, pocket calculators, routers, personal computers, printers and telephones. In Germany, around 12% of mobile phones end up in the process of formal treatment and in the USA only 5% (Perrine Chancerel, 2009). A reason for this can be that a large proportion of the mobile phones are stored by the users, even when they don't use them anymore. Additionally, small devices are also easier to throw away in bins which can play a role in the improper disposal of them (Cucchiella, D'Adamo, Lenny Koh, & Rosa, 2015). (European Union, 2012)

Besides the above mentioned EU categories, nowadays a new category emerges from the waist of photovoltaic panels that is used in academic papers about e-waste. Therefore, an additional category is added.

1.2.7 Extra category (not from the EU directive): photovoltaic panels (including converters)

Photovoltaic panels is the most important category in terms of what can happen when it is not known and defined how to manage the future e-waste stream. Photovoltaic panels are nowadays reaching a wide diffusion in industrial and private markets (Antonelli & Desideri, 2014). But, some of them in the '90s installed photovoltaic panels are now reaching their end of life. That's why recyclers now have to start deciding if recycling is feasible or if it is better to put them into landfills (Cucchiella et al., 2015).

In 2017 the quantity of e-waste in the EU mainly consisted of large equipment; 5.79 kilograms per inhabitant (KPI), small equipment; 5.42 KPI, and temperature exchange equipment; 3.25 KPI. The other 3 categories consisted together of; 3.76 KPI. Over the last 5 years, the biggest growing categories were temperature exchange equipment with an average of +3.36%, small equipment with +1.47% and large equipment with +1.25%. An exceptionally high growth rate would be seen when we would only look at photovoltaic panels (including converters), this is an average growth rate of 127.39% per year. Lamps has +0.98%, small IT and telecommunication equipment has +0.79% and screens has a negative growth rate of -2.26%. Forti et al. (2020) say that "this decline can be explained by the fact that, lately, heavy CRT monitors and screens have been replaced by lighter flat panel displays, resulting in a decrease of the total weight even as the number of pieces continue to grow."

2. LITERATURE REVIEW

2.1 Waste management

Technological breakthroughs have led to quick improvements in a wide range of EEE and manufacturing processes, this allowed for a global scale of production and distribution of affordable systems on a worldwide scale. This caused the shortening of use time of EEE since there is now a culture of rapidly changing high-tech products. The Covid-19 pandemic has also caused an even higher usage of electronic devices. The infrastructure and formalized mechanisms are unable to match the speed of e-waste production and are not developed enough to effectively collect, recycle and dispose of this increased e-waste. Above the environmental, health and social impact e-waste has, it also poses a threat to data privacy and security when not handled properly (Kapoor, Sulke, & Badiye, 2021; Tansel, 2017).

When the EEE has reached its end of life, the recycling process can be subdivided into three steps (P. Tanskanen & Takala, 2006). The first step is the collection of waste, also called the take-back when speaking of consumer recycling initiatives. This step has logistical challenges. The second step; pre-treatment of the e-waste is normally done by recycling companies. These companies sort the e-waste, and different materials are separated before selling them further. The recyclable materials are sold where the valuable materials can be recovered and refined. Then the last step happens where the e-waste that is not recyclable will be used for incineration which can be used for energy generation or it will be disposed of in landfills. The difficulty of the second and third steps can be influenced by the product design, which has an impact on the recycling efficiency and costs. That is why the product should be designed in a way that it can be recycled as efficiently as possible (Pia Tanskanen, 2013).

The product design improvements of recent years that increased the marketability and durability of the products caused more difficult recycling because of challenges with the separation of components. Surita and Tansel (2015) give the following example for this, "printed circuit boards (PCB), lamination of components and embedded systems increase the durability of components while reducing their size. However, structurally integrated materials make it difficult to disassemble and recover materials. In addition, coatings and sealants applied (e.g., polymers, siloxane-based materials) to improve the moisture resistance and durability of products need to be removed by acid dissolution or heat application".

To summarize; the main challenges for managing e-waste include the generation of high volumes, a large variety of products, lack of effective collection mechanisms and networks, presence of toxic materials, difficulty of separation (i.e., components being bolted, screwed, snapped, glued or soldered together), lack of financial incentives, and lack of adequate regulations (Lundgren, 2012).

2.2 E-waste impact

The large number of toxic chemicals that are associated with e-waste also causes concern. Research showed that toxic metals and polyhalogenated organics including polychlorinated biphenyls (PCBs) and polybrominated diphenyl ethers (PBDEs) can be released from e-waste (Czuczwa & Hites, 1984; Robinson, 2009).

Kiddee, Naidu, and Wong (2013) did extensive literature research about the impacts of e-waste on humans and the environment. Research on the recycling of e-waste confirmed that "significant levels of potentially toxic substances released during the recycling processes are building up in the environment. The potential hazards of persistent inorganic and organic contaminants (such as toxic (PCBs), (PBDEs), and metals) to the ecosystem and human health are expected to persist for many years to come". For landfills, there is also sufficient evidence that when they accept e-waste, it causes groundwater contamination (Schmidt, 2002) and that pollutants have the potential to migrate through soils and groundwater within and around landfill sites (Kasassi et al., 2008).

The metals included in e-waste can threaten human health when not appropriately managed. There are two different ways in which e-waste disposal has an impact on human health: 1. Issues with the food chain: byproducts enter the food chain. 2. Direct impact: occupational exposure to harmful compounds has a direct influence on workers who work in primitive recycling (Kiddee et al., 2013).

But e-waste also brings its opportunities, because the materials that are present in e-waste are valuable secondary resources (K. Baldé, Wang, Kuehr, & Huisman, 2015). The main components of e-waste which offer economic advantages include metals, plastics, glass and rare earth elements (Tansel, 2017). The top 10 materials that generate revenue when recovered from WEEE are; 1. Gold 50.4%, Copper 13.9%, Palladium 9.5%, Plastics 9.2%, Silver 3.6%, Aluminium 2.5%, Tin 2.0%, Barium 1.8%, Platinum 1.7%, Cobalt 1.6% (Cucchiella et al., 2015). This adds up to a total value of e-waste worldwide of €48 billion (K. Baldé et al., 2015). An important part of this value comes from the printed circuit board, which accounts for 40% of the metal value in e-waste (Golev, Schmeda-Lopez, Smart, Corder, & McFarland, 2016). Recovering materials during the recycling process also reduces energy consumption compared to materials that get mined (Cui & Forssberg, 2003).

2.3 Recycling per category

Each different category has products with different lifetime profiles that can change over time. The lifespan of a computer, for example, was in 1992 four and a half years but was estimated to be only two years in 2005 (Widmer et al., 2005). This means that every e-waste category has its own economic values, waste quantities, and potential environmental and health impacts when not recycled appropriately. That is why, there is a difference between the recycling technologies and collection processes of each category, as well as that the attitude consumers have when they dispose of their EEE, differs for each product (C. P. Baldé, V., Gray, Kuehr, & Stegmann, 2017). An example of this is the comparison Zeng and Li (2016) make between the recyclability (r/bit) of 9 different WEEE products. The value of R reveals the average recycling possibility of e-waste per unit mass, which ranges from 20 to 60/bit. From easiest to most difficult; refrigerator 54 ± 3.7 (temperature exchange equipment), desktop computer 52 ± 3.4 (small IT), duplicator 49 ± 8.5 (large equipment), washing machine 48 ± 6.1 (large equipment), air conditioner 43 ± 5.1 (temperature exchange equipment), printer 39 ± 5.6 (small IT), TV 37 ± 4.9 (screens), scanner 32 ± 0.07 (small IT), mobile phone 28 ± 0.99 (small IT). After each type of WEEE, you see the category it belongs to, this was found by use of the HS code and the UNU-KEYS (Forti, Baldé, & Kuehr, 2018), classification table and the link between UNU-Keys and HS code can be found in appendix D. Other research showed that the average treatment costs of small equipment and small IT is 240 €/t, temperature exchange equipment is 177 €/t, lamps is 400 €/t and of large household appliances it is 101€/t (European Commission et al., 2021) Large household appliances is one of the 10 old categories, which were later mostly split up in large equipment and temperature exchange equipment (appendix D).

Due to the existence of a higher concentration of precious and crucial metals, Cucchiella et al. (2015) found that smartphones (small IT), tablets (screens) and notebooks (screens) are the most valuable products. Small IT and screens and monitors contain over 80% of platinum group metals and gold and more than 70% of the silver in all categories of e-waste (Golev et al., 2016). For collecting, transporting and treating the WEEE of large and small equipment the CENELEC standards have been less used. For example, small equipment and small IT and telecommunication equipment are frequently treated in the same facilities where only between 8% and 19% of the facilities are compliant with the CENELEC standards. This also counts for large equipment and photovoltaic panels, while for temperature exchange equipment and lamps this was 46% and for screens it was 35%. That's why European Commission et al. (2021) say that when comparing the more homogeneous categories of lamps, screens and temperature exchange equipment to small and large appliances, additional EU WEEE treatment requirements are expected to cause major changes (environmental and health benefits and costs) for small and large equipment.

2.4 Legislation

Inside the EU there have been drafted and/or implemented several legislative documents that try to reduce the environmental impacts of WEEE.

2.4.1 RoHS Directive

The restriction of the use of certain hazardous substances in EEE (RoHS Directive 2002/95/EC) came into force in 2004. It prohibits the placing on the EU market of new EEE containing more than agreed levels of lead, cadmium, mercury, hexavalent chromium, polybrominated biphenyl and polybrominated diphenyl ether flame retardants (European Union, 2003a). The directive was subsequently recast (Directive 2011/65/EU) to expand the restriction of toxic substances to more types of EEE (European Union, 2011).

2.4.2 WEEE Directive

The WEEE Directive (directive 2002/96/EC) was established based on the principle of extended producer responsibility (EPR), mandating manufacturers and importers in the EU to take back their products from consumers and ensure that they are disposed of using environmentally sound methods (European Union, 2003b; Widmer et al., 2005). The objective of the directive is "as a first priority, the prevention of WEEE, and in addition, the reuse, recycling and other forms of recovery of such wastes so as to reduce the disposal of waste. It also seeks to improve the environmental performance of all operators involved in the life cycle of EEE, e.g. producers, distributors and consumers and in particular those operators directly involved in the treatment of WEEE" (European Union, 2003b). The directive also states that each member state is required to separately collect household WEEE at the annual rate of 4 kg/capita (European Union, 2003b). Challenges arose during the implementation phase, due to unequal development in operational and legislative progress in the member states. The experiences during the first years of the implementation indicated also some technical, legal and administrative problems (European Commission, 2008; Ylä-Mella, Poikela, Lehtinen, Keiski, & Pongrácz, 2014). To address some of these problems, the WEEE directive was revised in 2012. The recast directive (2012/19/EU) aimed to provide more clarity on the scope and set new collection targets based on WEEE generation in each member state (European Union, 2012; Ylä-Mella, Keiski, & Pongrácz, 2015). The recast WEEE Directive officially replaced Directive 2002/96/EC in 2014 and, from 2016, each member state has been required to collect, annually, a minimum of 45% of the average weight of EEE put on market (POM) in the preceding three years (Ylä-Mella et al., 2015). From 2019, the minimum required collection rate is 65% of the average EEE put on market in the 3 preceding years, or 85% of annually generated WEEE within each member state (European Union, 2012).

2.4.3 A new Circular Economy Action Plan

The EU wants to be climate neutral by 2050, a prerequisite for this is the transition to a circular economy. The action plan for this includes product design, encourages sustainable consumption, promotes circular economy and aims to prevent waste and retain resources in the EU economy for as long as possible. To attain this for e-waste, the European Commission presented a 'Circular Electronics Initiative' which includes, among others, the following actions: 1. devices have to be designed for energy efficiency and durability, reparability, upgradability, maintenance, reuse and recycling, 2. Right to repair, including obsolete software, 3. Improving the collection and treatment of WEEE, 4. Improving the collection and treatment of WEEE (European Commission, 2020).

3. METHODOLOGY

In order to answer the research question; which category of e-waste is going to be the major challenge for the EU, the future based on the current data has to be predicted. Time series modeling piqued the interest of the scientific community in recent decades. The main goal of time series modeling is to construct a model that represents the structure of the time series, this is done by collecting and studying past observations. A time series is a collection of data points that are measured over a period of time. It is mathematically defined as a set of vectors x(t),t = 0,1,2,... where t represents the time elapsed (Cochrane, 1997; Keith W. Hipel, 1994). The measurements obtained during an event are grouped in chronological order. Future values that will give a forecast are made using this model. That is why time series forecasting may be defined as the process of predicting the future by studying the past (Raicharoen, Lursinsap, & Sanguanbhokai, 2003). In practice, an appropriate model is fitted to the time series, and the associated parameters are calculated using known data. The process of finding a proper model that is fitting a time series is called time series analysis (Keith W. Hipel, 1994).

This research contains 2 different methods for time series forecasting, the first method used is an Autoregressive Integrated Moving Average (ARIMA) model, which was chosen due to its statistical properties as well as the methodological rigor. The second method, artificial neural network (ANN), is chosen because of its flexible nonlinear modeling capability. For both models, R was used to train, verify and forecast the model ARIMA

3.1 Collecting and preparing the data

The data used for these forecasts are from the Waste over Time (or WOT) Script (Van Straalen, 2016). Out of this data, the average kilograms of e-waste per inhabitant in the European Union was collected for each of the 6 categories and put in another dataset (this dataset can be found in Appendix A). To make sure there is enough data for the models the dataset was temporally disaggregated using the Denton-Cholette method made by E. B. Dagum and P. A. Cholette. This means that from the yearly e-waste data, quarterly data was disaggregated. Temporal disaggregation using this method is also one of the options European Statistical System (ESS) guidelines on temporal disaggregation, benchmarking and reconciliation (Dario Buono, 2018) advice. The temporal disaggregation was done by using the tempdisagg pack (Sax & Steiner, 2013). In Appendix E you can see how this was done in R.
In the dataset the used category 4 is split up in:
4a. Large equipment (excluding photovoltaic panels)
4b. Photovoltaic panels (incl. converters)

3.2 ARIMA model

The Autoregressive Integrated Moving Average (ARIMA) model is widely used and one of the most important stochastic time series methods. The model is based on the premise that the time series under consideration is linear and follows a known statistical distribution. Although ARIMA models are quite flexible in that they can represent several different types of time series, i.e., pure autoregressive (AR), pure moving average (MA) and combined AR and MA (ARMA) series, their major limitation is the pre-assumed linear form of the model. That is, a linear correlation structure is assumed among the time series values and therefore, no nonlinear patterns can be captured by the ARIMA model (G. P. Zhang, 2003). Because the ARIMA model and its variants are based on the Box-Jenkins principle (G.E.P. Box, 1970; Keith W. Hipel, 1994) they are frequently referred to as Box-Jenkins models. In the model; p, d, and q are integers higher than or equal to zero that represent the order of the model's autoregressive, integrated, and moving average components, respectively.

The Box-Jenkins methodology makes no assumptions about the particular patterns in past data of the series to be forecasted. It instead uses a three-step iterative strategy of model identification, parameter estimation, and diagnostic checking to determine the best parsimonious model of ARIMA models (G.E.P. Box, 1970; G. P. Zhang, 2003)[6, 8, 12, 27]. This three-step approach is done multiple times until a suitable model is found. The model can then be used to forecast future values of the time series. In figure 1 you see the steps of the Box-Jenkins method.

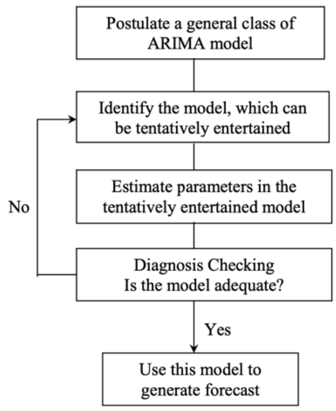

Figure 1. The Box-Jenkins methodology for optimal model selection (Adhikari & Agrawal, 2013)

3.3 Artificial Neural Network

Artificial Neural Networks (ANNs) have become extremely popular for prediction and forecasting in a number of areas, including finance, power generation, medicine, water resources and environmental science (Maier & Dandy, 2000). Research into applications of ANNs has blossomed since the introduction of the backpropagation training algorithm for feedforward ANNs in 1986 (Rumelhart, Hinton, & Williams, 1986).

Applied to time series ANNs are excellent for forecasting problems, this is because they don't need any presumptions of the statistical distribution followed by the data, but still are inherently capable of non-linear modeling. This means that the model is adaptively formed on the data that's given. ANNs, like human brains, attempt to discover regularities and patterns in input data, learn from experience, and then deliver generalized results based on their previously existing knowledge. Although ANNs were developed primarily for biological reasons, they have since been used in a wide range of applications, most notably forecasting and classification (J.M. Kihoro, 2004).

The following sections will highlight the key characteristics of ANNs that make them popular for time series analysis and forecasting. ANNs are data-driven and self-adaptive by nature There is no need to describe a specific model form or make any prior assumptions about the statistical distribution of the data; the model that is desired is constructed adaptively depending on the data attributes. This strategy is highly effective in many real scenarios where no theoretical direction for an acceptable data generation process is given. Second, ANNs are intrinsically nonlinear, making them more accurate and practical in modeling complicated data patterns than standard linear approaches do. Finally, ANNs are universal approximators that can accurately approximate a wide range of functions. In the literature, there are numerous ANN forecasting models. The most frequent and widely used are multi-layer perceptron's (MLPs), which have a single hidden layer Feed Forward Network (FNN) (G. Zhang, Eddy Patuwo, & Y. Hu, 1998; G. P. Zhang, 2003).

4. TRAINING

4.1 ARIMA model

For each category, the optimal model was found using the box-Jenkins method. This was done by following a three-step approach of model identification, parameter estimation and diagnostic checking.

1. The first step in identifying the best model is checking if the variable is stationary or non-stationary. In all categories, this was non-stationary, because there can be a trend seen. This means that the ARIMA model instead of the ARMA model will be used in all categories. After this, the correlogram was checked to determine P and Q. This was done using the Autocorrelation Function (ACF) and the Partial Autocorrelation Function (PACF). From there, the possible model parameters for AR and MA are found. For small equipment, this means that AR has to be 1, and MA can be between 1 and 20 (in APPENDIX B is a further explanation of how this was found).
2. For each category, the optimal parameters were found by looking at the lowest Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), lowest Root Mean Squared Error (RMSE), Mean Absolute Error (MAE) and the Mean Absolute Percentage Error (MAPE). For example, in the case of small equipment, this means an ARIMA (1,1,5) has the best model evaluation.
3. The last step is the diagnostics checking of model adequacy, this is essentially to see if the model assumptions about errors are met. It was checked by looking at the ACF of the residuals (G. P. Zhang, 2003).

4.2 Artificial Neural Network model

For the neural network, the dataset was split up into a training set (the first 90% of the data) and a test set (the last 10% of the data). In this way, the model can first be created based on the training data and afterward be checked on the test data. Three different models were tested on this data, after which the MAE between the output of the model and test data was calculated. The first model is a neural network autoregression (nnetar) from the forecasting package in R. This was run as a standard model and with some tweaks, a BoxCox.lambda function was added to find the best possible lambda. The second and third models are from the package nnfor, these are a Multilayer Perceptrons (MLP) model and an Extreme Learning Machine (ELM) model. The MLP model was run as a standard model and with the tweak of finding the optimal amount of hidden notes using the hd.auto.type function. The ELM model was only run as a standard model. After finding the model with the best MAE score, the model was applied to the whole dataset. In the case of small equipment this means that the standard MLP fit with 5 hidden nodes and 20 repetitions model gives the best MAE;

Table 1. Comparison of the MAE of each model

Model	nnetar	MLP	ELM	nnetar2	MLP2
MAE	0.0667	0.0225	0.0521	0.0679	0.0252

How the models were made and how the best one was chosen are shown in Appendix C.

5. FORECASTS

The forecasts made by the ARIMA model and the ANN model can be seen in figures 4 and 5. The uninterrupted lines are from the data gained from the (WOT) script (from 1993 to 2017) and the dashed lines are the forecasted data from (2018 to 2027) predicted by the models.

5.1 ARIMA

Out of the forecast generated by the ARIMA model can be seen that the biggest category of e-waste in 2027 is still large equipment (excluding PV panels) with 6.15 kilograms per inhabitant (KPI). This means that it is still bigger than small equipment with 5.93 KPI. This is because the average increase of e-waste per year is 0.95% for small equipment, but 0.70% for large equipment. The average increase was 2.42% for temperature exchange equipment and 0.39% for small IT. Screens was the only category that has seen a decrease with an average of -4.90% per year. Between lamps and PV panels happened a big change, while screens increased by only an average of 0.23%, PV panels increased by an average of 28.51% per year. Because of this PV panels is now almost the bigger category with 0.1891 KPI, compared to the 0.2205 KPI of lamps.

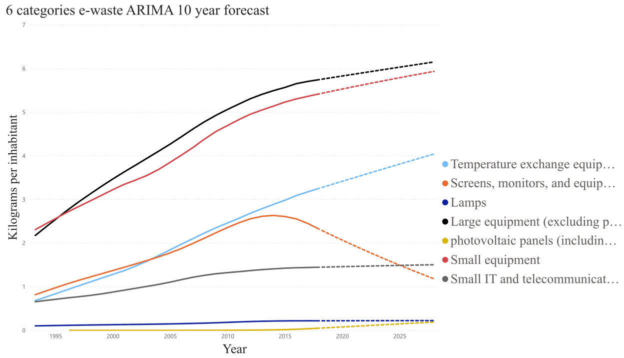

Figure 2. 6 categories of e-waste ARIMA 10-year forecast

5.2 Artificial Neural Network

Out of the forecast generated by the ANN model can be seen that large equipment with 6.19 KPI just stays bigger than small equipment with 6.13 KPI. This can be explained by the average increase of 0.79% for large equipment per year, compared to small equipment's average increase of 1.31% per year. The average increase per year for temperature exchange equipment was 3.09% and small IT was 0.46%, while screens has dropped down to 0.87 KPI having an average decrease of -6.22% per year. PV panels with 0.2565 KPI are now bigger lamps with 0.2230 KPI.

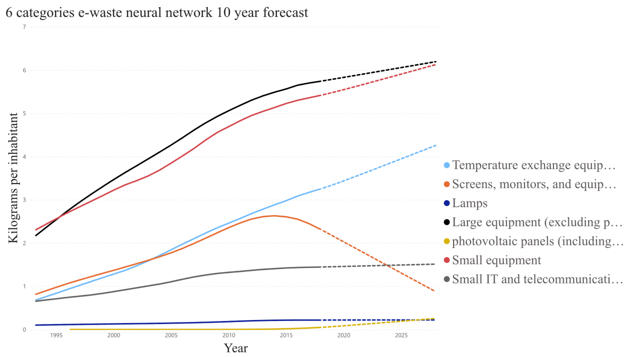

Figure 3. 6 categories of e-waste neural network 10-year forecast

6. DISCUSSION

To determine the category of e-waste that is going to be the major challenge for the EU, it was researched what the differences between the e-waste categories are in recyclability, profitability and how good recycling facilities follow the EU directives about e-waste. There were also 2 forecasts about the amount of e-waste per category in 2027. The models predict that the KPI of every category except screens will increase over the years, this means that the recycling infrastructure needs to grow with it. Knowing that the recycling infrastructure cannot handle the amount of e-waste that is currently produced as seen in chapter 2, e-waste is becoming a bigger challenge for the EU in the near future. To solve this, there need to come solutions to effectively collect, recycle and dispose of this increase in e-waste. To attain the circular economy plan in 2050, for e-waste, legislation from the EU needs to be improved and recycling facilities need to be better controlled on their recycling standards. It needs to be more incentivized to recycle the e-waste, by either increasing the penalties for disposing e-waste or rewarding the recycling.

6.1 Comparison

In the forecasts is seen that although the general trend of the ARIMA model and the ANN model are the same, there are still differences between the output. This happens because the ARIMA model uses very strict assumptions about the data generation process, while the ANN model is more flexible.

In table 2 the categories are ranked on KPI in 2027, for this the average of the ARIMA and ANN output was used. When looking only at the ANN model the ranking stays the same, but for the ARIMA model numbers 6 and 7 are changed. Out of this ranking can be concluded that the KPI of small equipment and large equipment stand out above the rest.

Table 2. Ranking the categories on kilograms per inhabitant.

Category	*2017*	*2027 ARIMA KPI*	*2027 ANN KPI*	*Ranking*
Large equipment (excluding photovoltaic panels)	*5.7420*	*6.1459*	*6.1931*	*1*
Small equipment	*5.4158*	*5.9296*	*6.1252*	*2*
Temperature exchange equipment	*3.2524*	*4.0387*	*4.2563*	*3*
Small IT and telecommunication equipment	*1.4453*	*1.5020*	*1.5118*	*4*
Screens	*2.3159*	*1.1804*	*0.8754*	*5*
Photovoltaic panels	*0.0491*	*0.1891*	*0.2565*	*6*
Lamps	*0.2181*	*0.2230*	*0.2205*	*7*

In table 3 the categories are ranked on the average increase per year, for this the average of the ARIMA and ANN increase was used. For both models, the ranking stays the same when looked at them separately. At the top can be seen that the photovoltaic panels have a huge increase. But when compared to the rest (excluding photovoltaic panels), temperature exchange equipment and small equipment have a high average increase.

Table 3. Ranking the categories on average increase

Category	*2017*	*ARIMA 2027*	*ANN 2027*	*Ranking*
Photovoltaic panels (incl. converters)	*127.39%*	*28.51%*	*42.23%*	*1*
Temperature exchange equipment	*3.36%*	*2.42%*	*3.09%*	*2*
Small equipment	*1.47%*	*0.95%*	*1.31%*	*3*
Large equipment (excluding photovoltaic panels)	*1.25%*	*0.70%*	*0.79%*	*4*
Small IT and telecommunication equipment	*0.79%*	*0.39%*	*0.46%*	*5*
Lamps	*0.98%*	*0.23%*	*0.11%*	*6*
Screens	*-2.26%*	*-4.90%*	*-6.22%*	*7*

For the recyclability of e-waste, small IT products are the most difficult to recycle. Small IT and small equipment are often recycled in the same facilities, so the difficulty probably also counts for small equipment. Below is a comparison of the average costs of recycling for each category that was found by a study of the European Commission. For screens and photovoltaic panels, no data was found. Lamps are the most expensive, followed by small equipment and small IT.

Table 4. Ranking the categories for cost of recycling (European Commission et al., 2021)

Category	*Costs of recycling*	*Ranking*
Lamps	*400 €/t*	*1*
Small IT and telecommunication equipment	*240 €/t*	*2*
Small equipment	*240 €/t*	*2*
Temperature exchange equipment	*177 €/t*	*4*
Large equipment (excluding photovoltaic panels)	*101 €/t*	*5*
Screens	*Not known*	-
Photovoltaic panels (incl. converters)	*Not known*	-

6.2 Limitations

A limitation of this research is the data available about the amount of e-waste. The Waste of Time script uses the 'apparent consumption method', and the 'sales lifetime approach'. Briefly put, this means estimating the physical sales by production plus imports minus exports of the product. The weight of those sales is then integrated with the curves of the expected lifespan of electronic and electrical equipment. This enables forecasting of the future volumes of e-waste as a function of time. Another limitation is that for the forecasting models, only historical data on the kilograms per inhabitant was used. Another option would be looking at the total number of e-waste products. Research on the profitability and recyclability of e-waste has mostly been done for metals, plastics, glass and rare earth elements. Towards certain products research has been done, but only limited. During this research, there was no data found on the data of recyclability and profitability over the range of the 6 categories defined by the EU. Only one study about the costs of recycling from some categories of e-waste was found. This makes the conclusions about these aspects limited.

6.3 Further research

Further research could be done when the data of recent years would be gathered. When the new data would be available this could be compared to the forecasts made to see how accurate they are, or new forecasts could be made upon this new data. Furthermore, models not based on the kilograms per inhabitant but on the quantity of e-waste could be explored. The focus of this research was mainly a forecast about e-waste, but further research on the effect legislation has per category or a better overview of recyclability and profitability per category could be built on this paper.

7. CONCLUSION

Based on the forecasts and the literature research, the category of e-waste that is going to be the major challenge for the EU in the years to come is small equipment. When following the current trend of the ARIMA model and the ANN model it will eventually become the biggest category of e-waste. Small equipment is also the second most expensive category to recycle, reasons for this are the big challenges due to the variety of products in this category. Small equipment is the category where the CENELEC standards for the collection and transport are the least implemented, making it the category that needs the most improvement. Although small equipment is the category that is going to be the major challenge for the EU, photovoltaic panels should also be carefully watched. This is because of the predicted average 28.51% increase per year according to the ARIMA model and the predicted average 42.23% increase per year according to the ANN model, the unknow average recycling costs also causes concerns.

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APPENDIX

Appendix A: dataset used for the predictions.

A.1 Original dataset

Year	EU6PV_1	EU6PV_2	EU6PV_3	EU6PV_4a	EU6PV_4b	EU6PV_5	EU6PV_6
1993	0,747094	0,88446	0,105573	2,330598	0	2,415444	0,67891
1994	0,836265	0,97356	0,109979	2,53695	0	2,557346	0,70948
1995	0,927485	1,061522	0,114243	2,742623	1,05E-08	2,701456	0,741814
1996	1,017027	1,142878	0,118029	2,9357	1,94E-07	2,831342	0,768645
1997	1,105022	1,218842	0,121625	3,117641	1,07E-06	2,959404	0,797576
1998	1,193728	1,293925	0,125253	3,294351	3,31E-06	3,088537	0,833451
1999	1,280753	1,368087	0,12872	3,464823	7,68E-06	3,220204	0,875345
2000	1,367271	1,444312	0,132147	3,628638	1,51E-05	3,343327	0,91922
2001	1,471607	1,521156	0,135288	3,785004	2,67E-05	3,441648	0,963276
2002	1,585297	1,599307	0,138561	3,942658	4,47E-05	3,549676	1,007235
2003	1,710642	1,682765	0,142473	4,102729	7,45E-05	3,68527	1,051284
2004	1,843135	1,772957	0,147145	4,264404	0,000134	3,847399	1,103132
2005	1,975127	1,875721	0,152452	4,435429	0,000252	4,014056	1,161633
2006	2,101599	1,990741	0,158059	4,612856	0,000453	4,187918	1,216105
2007	2,229964	2,111387	0,164816	4,77674	0,000759	4,38001	1,259522
2008	2,349954	2,234705	0,173043	4,925008	0,001201	4,55424	1,296245
2009	2,458088	2,354126	0,182409	5,058021	0,001841	4,689959	1,321336
2010	2,565912	2,463011	0,192309	5,182872	0,00279	4,826526	1,342805
2011	2,680133	2,554339	0,201211	5,304185	0,004269	4,949562	1,367872
2012	2,784057	2,611085	0,207929	5,404268	0,00666	5,045531	1,390277
2013	2,883397	2,630239	0,212834	5,488646	0,010479	5,133387	1,407315
2014	2,978636	2,606773	0,215993	5,562224	0,016243	5,22629	1,423075
2015	3,085239	2,551616	0,218014	5,649536	0,024334	5,299743	1,433191
2016	3,172003	2,447419	0,218198	5,70064	0,035183	5,358663	1,439151
2017	3,252416	2,315945	0,218092	5,742006	0,04908	5,415775	1,445331

A.2 Temporal disaggregated dataset

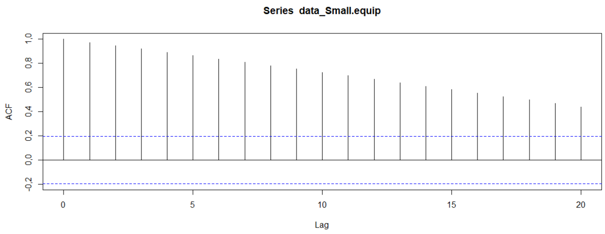
EU6_PV1 (	EU6_PV2 (	EU6_PV3 (	EU6_PV4a	EU6_PV4b	EU6_PV5 (	EU6_PV6 (
0,681567	0,815014	0,101948	2,172902		2,305964	0,654704
0,703409	0,838162	0,103157	2,225467		2,342457	0,662773
0,725252	0,861311	0,104365	2,278033		2,378951	0,670842
0,747094	0,88446	0,105573	2,330598		2,415444	0,67891
0,769387	0,906735	0,106675	2,382186		2,450919	0,686553
0,791679	0,92901	0,107776	2,433774		2,486395	0,694195
0,813972	0,951285	0,108878	2,485362		2,52187	0,701838
0,836265	0,97356	0,109979	2,53695		2,557346	0,70948
0,85907	0,995551	0,111045	2,588368		2,593373	0,717564
0,881875	1,017541	0,112111	2,639786		2,629401	0,725647
0,90468	1,039531	0,113177	2,691205		2,665429	0,733731
0,927485	1,061522	0,114243	2,742623		2,701456	0,741814
0,94987	1,081861	0,11519	2,790892	5,64E-08	2,733928	0,748522
0,972256	1,1022	0,116136	2,839161	1,02E-07	2,766399	0,75523
0,994642	1,122539	0,117083	2,887431	1,48E-07	2,798871	0,761938
1,017027	1,142878	0,118029	2,9357	1,94E-07	2,831342	0,768645
1,039026	1,161869	0,118928	2,981185	4,13E-07	2,863358	0,775878
1,061025	1,18086	0,119827	3,02667	6,32E-07	2,895373	0,783111
1,083023	1,199851	0,120726	3,072155	8,51E-07	2,927389	0,790344
1,105022	1,218842	0,121625	3,117641	1,07E-06	2,959404	0,797577
1,127198	1,237613	0,122532	3,161818	1,63E-06	2,991687	0,806545
1,149375	1,256384	0,123439	3,205996	2,19E-06	3,02397	0,815514
1,171551	1,275154	0,124346	3,250173	2,75E-06	3,056253	0,824482
1,193728	1,293925	0,125253	3,294351	3,31E-06	3,088537	0,833451
1,215484	1,312466	0,12612	3,336969	4,40E-06	3,121453	0,843925
1,23724	1,331006	0,126986	3,379587	5,50E-06	3,15437	0,854398
1,258997	1,349547	0,127853	3,422205	6,59E-06	3,187287	0,864872
1,280753	1,368087	0,12872	3,464823	7,68E-06	3,220204	0,875345
1,302382	1,387144	0,129577	3,505777	9,54E-06	3,250985	0,886314
1,324012	1,4062	0,130434	3,546731	1,14E-05	3,281765	0,897283
1,345642	1,425256	0,13129	3,587684	1,32E-05	3,312546	0,908251
1,367271	1,444312	0,132147	3,628638	1,51E-05	3,343327	0,91922
1,393355	1,463523	0,132932	3,667729	1,80E-05	3,367908	0,930234
1,419439	1,482734	0,133717	3,706821	2,09E-05	3,392488	0,941248
1,445523	1,501945	0,134503	3,745913	2,38E-05	3,417068	0,952262
1,471607	1,521156	0,135288	3,785004	2,67E-05	3,441648	0,963276
1,50003	1,540694	0,136106	3,824418	3,12E-05	3,468655	0,974265
1,528452	1,560231	0,136924	3,863831	3,57E-05	3,495662	0,985255
1,556874	1,579769	0,137742	3,903245	4,02E-05	3,522669	0,996245
1,585297	1,599307	0,138561	3,942658	4,47E-05	3,549676	1,007235
1,616633	1,620171	0,139539	3,982676	5,22E-05	3,583574	1,018247
1,647969	1,641036	0,140517	4,022694	5,96E-05	3,617473	1,029259
1,679306	1,661901	0,141495	4,062711	6,71E-05	3,651371	1,040271
1,710642	1,682765	0,142473	4,102729	7,45E-05	3,68527	1,051284
1,743765	1,705313	0,143641	4,143148	8,95E-05	3,725802	1,064246
1,776888	1,727861	0,144809	4,183566	1,04E-04	3,766335	1,077208
1,810012	1,750409	0,145977	4,223985	1,19E-04	3,806867	1,09017
1,843135	1,772957	0,147145	4,264404	1,34E-04	3,847399	1,103132
1,876133	1,798648	0,148472	4,30716	1,64E-04	3,889063	1,117757
1,909131	1,824339	0,149799	4,349917	1,93E-04	3,930728	1,132383
1,942129	1,85003	0,151125	4,392673	2,23E-04	3,972392	1,147008
1,975128	1,875721	0,152452	4,435429	2,52E-04	4,014056	1,161633
2,006745	1,904476	0,153854	4,479786	3,02E-04	4,057522	1,175251
2,038363	1,933231	0,155256	4,524143	3,52E-04	4,100987	1,188869
2,069981	1,961986	0,156658	4,5685	4,02E-04	4,144452	1,202487
2,101599	1,990741	0,158059	4,612856	4,53E-04	4,187918	1,216105
2,13369	2,020902	0,159748	4,653827	5,29E-04	4,235941	1,226959
2,165781	2,051064	0,161438	4,694798	6,06E-04	4,283964	1,237813
2,197873	2,081226	0,163127	4,735769	6,82E-04	4,331987	1,248668
2,229964	2,111387	0,164816	4,77674	7,59E-04	4,38001	1,259522
2,259962	2,142217	0,166873	4,813807	8,69E-04	4,423567	1,268703
2,289959	2,173046	0,16893	4,850874	9,80E-04	4,467125	1,277884
2,319957	2,203876	0,170987	4,887941	1,09E-03	4,510682	1,287065
2,349954	2,234705	0,173044	4,925008	1,20E-03	4,55424	1,296245
2,376988	2,26456	0,175385	4,958261	1,36E-03	4,58817	1,302518
2,404021	2,294416	0,177726	4,991514	1,52E-03	4,622099	1,308791
2,431055	2,324271	0,180068	5,024768	1,68E-03	4,656029	1,315064
2,458088	2,354126	0,182409	5,058021	1,84E-03	4,689959	1,321337
2,485044	2,381347	0,184884	5,089234	2,08E-03	4,724101	1,326704
2,512	2,408569	0,187359	5,120447	2,32E-03	4,758243	1,332071
2,538956	2,43579	0,189834	5,15166	2,55E-03	4,792384	1,337438
2,565912	2,463011	0,192309	5,182872	2,79E-03	4,826526	1,342805
2,594467	2,485843	0,194534	5,2132	3,16E-03	4,857285	1,349072
2,623023	2,508675	0,19676	5,243529	3,53E-03	4,888044	1,355339
2,651578	2,531507	0,198986	5,273857	3,90E-03	4,918803	1,361605
2,680133	2,55434	0,201211	5,304185	4,27E-03	4,949562	1,367872
2,706114	2,568526	0,202891	5,329205	4,87E-03	4,973554	1,373473
2,732095	2,582712	0,20457	5,354226	5,46E-03	4,997546	1,379074
2,758076	2,596899	0,20625	5,379247	6,06E-03	5,021538	1,384676
2,784057	2,611085	0,207929	5,404268	6,66E-03	5,045531	1,390277
2,808892	2,615874	0,209156	5,425362	7,61E-03	5,067495	1,394536
2,833727	2,620662	0,210382	5,446457	8,57E-03	5,089459	1,398796
2,858562	2,625451	0,211608	5,467551	9,52E-03	5,111423	1,403055
2,883397	2,630239	0,212834	5,488646	1,05E-02	5,133387	1,407315
2,907207	2,624373	0,213624	5,50704	1,19E-02	5,156613	1,411255
2,931017	2,618506	0,214414	5,525435	1,34E-02	5,179839	1,415195
2,954827	2,612639	0,215204	5,543829	1,48E-02	5,203065	1,419135
2,978636	2,606773	0,215993	5,562224	1,62E-02	5,22629	1,423075
3,005287	2,592984	0,216499	5,584052	1,83E-02	5,244654	1,425604
3,031938	2,579195	0,217004	5,60588	2,03E-02	5,263017	1,428133
3,058588	2,565406	0,217509	5,627708	2,23E-02	5,28138	1,430662
3,085239	2,551616	0,218014	5,649536	2,43E-02	5,299743	1,433191
3,10693	2,525567	0,21806	5,662312	2,70E-02	5,314473	1,434681
3,128621	2,499518	0,218106	5,675088	2,98E-02	5,329203	1,436171
3,150312	2,473469	0,218152	5,687864	3,25E-02	5,343933	1,437661
3,172003	2,447419	0,218198	5,70064	3,52E-02	5,358663	1,439151
3,192106	2,414551	0,218171	5,710982	3,87E-02	5,372941	1,440696
3,212209	2,381682	0,218145	5,721323	4,21E-02	5,387219	1,442241
3,232313	2,348814	0,218119	5,731665	4,56E-02	5,401497	1,443786
3,252416	2,315945	0,218092	5,742006	4,91E-02	5,415775	1,445332

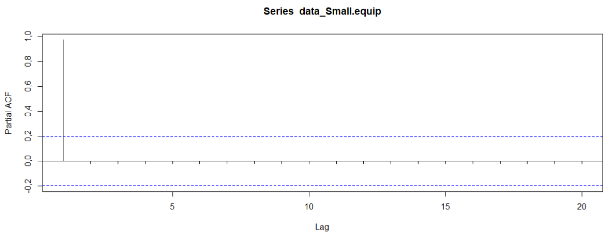
Appendix B: ARIMA model 6 categories e-waste.

B.1 Script written for the ARIMA model:

```
library(zoo)
library(forecast)
library(nnfor)
library(directlabels)
library(ggplot2)
library(tsibble)
data_Small.equip <- Thesis.data.set$EU6_PV5.quarter
acf_Small.equip <- acf(data_Small.equip)
acf_Small.equip

pacf_Small.equip <- pacf(data_Small.equip)
pacf_Small.equip

Fit_Small.equip <- arima(data_Small.equip, order = c(1,1,5))
summary(Fit_Small.equip)
BIC(Fit_Small.equip)
res <- Fit_Small.equip$residuals
acf(res)
Forecast_Small.equip <- forecast(Fit_Small.equip, h =40)
summary(Forecast_Small.equip)
autoplot(Forecast_Small.equip) + ylab("KPI") + theme_grey() + labs(title = "Forecast Small.equip")
```

Step 1: Check the ACF and PACF of the data

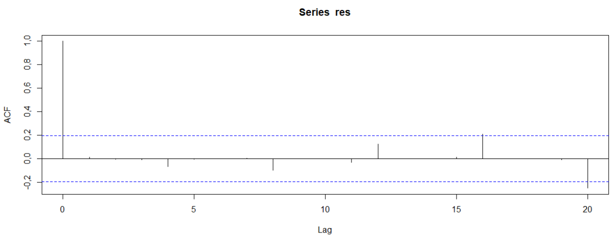




Step 2: check the best error measures

```
> summary(Fit_Small.equip)

Call:
arima(x = data_Small.equip, order = c(1, 1, 4))

Coefficients:
         ar1     ma1     ma2     ma3     ma4
      0,9955  0,0010  0,0009  0,0000  0,6449
s.e.  0,0052  0,0801  0,0787  0,0808  0,0813

sigma^2 estimated as 2,97e-06:  log likelihood = 485,59,  aic = -959,17

Training set error measures:
                        ME        RMSE         MAE         MPE       MAPE       MASE       ACF1
Training set -9,785973e-06 0,001730137 0,000805311 0,001283113 0,02156715 0,02563686 0,01238672
> BIC(Fit_Small.equip)
[1] -943,5999
```

Step 3: diagnose the model with the ACF of the residuals



B.2 Best model for each category

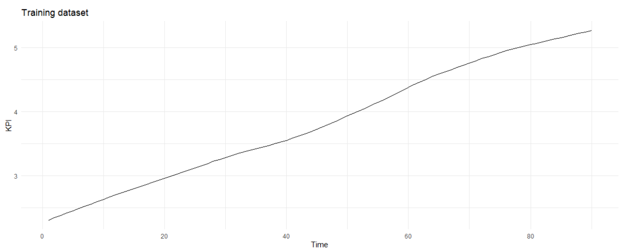
Category	*Best model*
Temperature exchange equipment (EU6PV_1)	*ARIMA(1,1,2)*
Screens (EU6PV_2)	*ARIMA(1,1,4)*
Lamps (EU6PV_3)	*ARIMA(1,1,4)*
Large equipment (excluding photovoltaic panels) (EUP6PV_4a)	*ARIMA(1,1,4)*
Photovoltaic panels (incl. converters) (EU6PV_4b)	*ARIMA(1,2,1)*
Small equipment (EU6PV_5)	*ARIMA(1,1,5)*
Small IT and telecommunication equipment (EU6PV_6)	*ARIMA(1,1,4)*

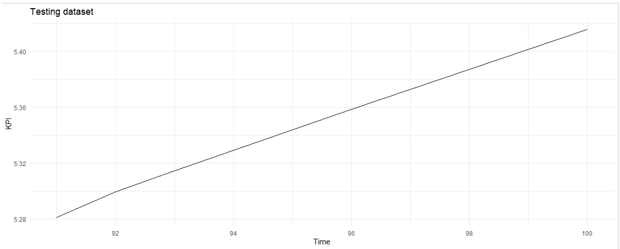
Appendix C: Feed-forward Neural Network model 6 categories e-waste.

C.1 Script written for the neural network model:

```
library(zoo)
library(forecast)
library(nnfor)
library(directlabels)
library(ggplot2)
library(tsibble)
#Now import dataset: average 6 categories quarter.csv
#changing the data set to a time series and selecting the training en test data.
Small.equip = (average.6.categories.quarter$EU6_PV5.quarter)
Small.equip = ts(Small.equip, start = 1, frequency = 1)
Small.equip.train <- window(Small.equip, end = 90)
autoplot(Small.equip.train) + ylab("KPI") + ggtitle("Training dataset") + theme_minimal()

Small.equip.test <- window(Small.equip, start = 91)
autoplot(Small.equip.test) + ylab("KPI") + ggtitle("Testing dataset") + theme_minimal()

#option 1 nnetar
Small.equip.fit.nnetar <- nnetar(Small.equip.train)
Small.equip.fcst.nnetar <- forecast(Small.equip.fit.nnetar, h = 10)
autoplot(Small.equip.test) + autolayer(Small.equip.fcst.nnetar, series = "nnetar Forecast", linetype = "dashed") +theme_minimal() + ylab("KPI")
autoplot(Small.equip.fcst.nnetar)
Small.equip.fit.nnetar

#option 2 nnetar
Small.equip.fit.nnetar2 <- nnetar(Small.equip.train, lambda = BoxCox.lambda(Small.equip.train))
Small.equip.fcst.nnetar2 <- forecast(Small.equip.fit.nnetar2, h = 10)
autoplot(Small.equip.test) + autolayer(Small.equip.fcst.nnetar2, series = "nnetar w/ BoxCox Forecast", linetype = "dashed") +theme_minimal() + ylab("KPI")
autoplot(Small.equip.fcst.nnetar2)
Small.equip.fit.nnetar2
summary(Small.equip.fcst.nnetar2)

#option 1 MLP
Small.equip.fit.mlp <- mlp(Small.equip.train)
Small.equip.fcst.mlp <- forecast(Small.equip.fit.mlp, h = 10)
autoplot(Small.equip.test) + autolayer(Small.equip.fcst.mlp, series = "mlp Forecast", linetype = "dashed") +theme_minimal() + ylab("KPI")
autoplot(Small.equip.fcst.mlp)
Small.equip.fit.mlp

#option 2 MLP
Small.equip.fit.mlp2 <- mlp(Small.equip.train, hd.auto.type = "valid")
Small.equip.fcst.mlp2 <- forecast(Small.equip.fit.mlp2, h = 10)
autoplot(Small.equip.test) + autolayer(Small.equip.fcst.mlp2, series = "mlp w/ opt. hidden notes Forecast", linetype = "dashed") +theme_minimal() + ylab("KPI")
autoplot(Small.equip.fcst.mlp2)
Small.equip.fit.mlp2
summary(Small.equip.fcst.mlp2)

#option 1 ELM
Small.equip.fit.elm <- elm(Small.equip.train)
Small.equip.fcst.elm <- forecast(Small.equip.fit.elm, h = 10)
autoplot(Small.equip.test) + autolayer(Small.equip.fcst.elm, series = "elm Forecast", linetype = "dashed") +theme_minimal() + ylab("KPI")
autoplot(Small.equip.fcst.elm)
Small.equip.fit.elm

#establish tibble to contain predictions
mae <- tibble(Test = Small.equip.test, nnetar = Small.equip.fcst.nnetar$mean, MLP = Small.equip.fcst.mlp$mean, ELM = Small.equip.fcst.elm$mean)

#Calculate abs.error
mae$ae.nnetar <- with(mae, abs(nnetar - Test))
mae$ae.MLP <- with(mae, abs(MLP - Test))
mae$ae.ELM <- with(mae, abs(ELM - Test))

#Calculate MAE
mae.score <- apply(mae, 2, mean) [5:7]
names(mae.score) <- c("MAE.nnetar", "MAE.MLP", "MAE.ELM")
mae.score

#repeat the process from MAE <- tibble.... , but now with nnetar2$mean, and mlp2$mean.

#the model with the best MAE score is then applied on the full data set.
Small.equip.fit <- mlp(Small.equip, model = Small.equip.fit.mlp)
Small.equip.fcst <- forecast(Small.equip.fit, h = 40)
autoplot(Small.equip.fcst) + ylab("KPI") + theme_grey() + labs(title = "Forecast Small.equip Equipment")
summary(Small.equip.fcst)
```

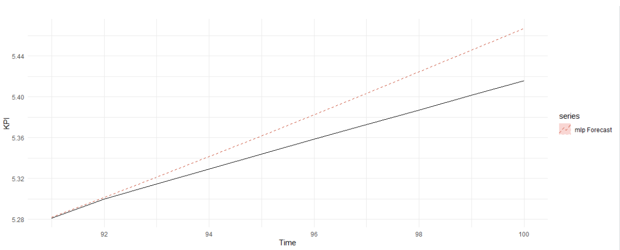
Step 1: create test set and training set





Step 2: compare the know data to the model prediction

Visual output comparison mlp



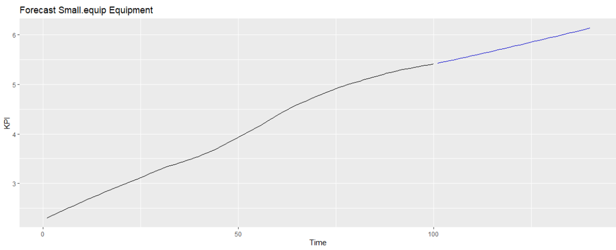
Compare the MAE of each model

MAE.nnetar	MAE.MLP	MAE.ELM
0.06668837	0.02254374	0.05205347

Best model is MLP fit with 5 hidden nodes and 20 repetitions.

Step 3: apply this model on the know dataset to forecast

```
Forecast method: mlp

Model Information:
NULL

Error measures:
                        ME        RMSE          MAE           MPE       MAPE       MASE       ACF1
Training set -4,875588e-05 0,001997186 0,0009695171 -8,951978e-05 0,02425615 0,03052106 0,02252031

Forecasts:
    Point Forecast
101       5,430741
102       5,446250
103       5,462195
104       5,478508
105       5,495127
106       5,512006
107       5,529104
108       5,546390
109       5,563837
110       5,581424
111       5,599131
112       5,616943
113       5,634884
114       5,652941
115       5,671076
116       5,689280
117       5,707544
118       5,725862
119       5,744228
120       5,762636
121       5,781081
122       5,799559
123       5,818067
124       5,836601
125       5,855158
126       5,873735
127       5,892332
128       5,910944
129       5,929571
130       5,948212
131       5,966863
132       5,985526
133       6,004197
134       6,022877
135       6,041564
136       6,060257
137       6,078956
138       6,097661
139       6,116370
140       6,135084
```



C.2 Best model for each category

Category	*Best model*
Temperature exchange equipment (EU6PV_1)	*ELM fit with 86 hidden nodes and 20 repetitions.*
Screens (EU6PV_2)	*MLP with 5 hidden nodes and 20 repetitions.*
Lamps (EU6PV_3)	*nnetar with an average of 20 networks, each of which is a 1-1-1 network with 4 weights.*
Large equipment (excluding photovoltaic panels) (EUP6PV_4a)	*MLP with 5 hidden nodes and 20 repetitions.*
Photovoltaic panels (incl. converters) (EU6PV_4b)	*The best model was: MLP with 5 hidden nodes and 20 repetitions.*
Small equipment (EU6PV_5)	*The best model was: MLP with 5 hidden nodes and 20 repetitions.*
Small IT and telecommunication equipment (EU6PV_6)	*The best model was: MLP with 5 hidden nodes and 20 repetitions.*

Appendix D: classification table and link between UNU-Keys and HS code.

D.1 Description of the UNU product classification and its correlation to other e-waste classifications.

UNU KEY	DESCRIPTION	EEE CATEGORY UNDER EU-6	EEE CATEGORY UNDER EU-10
0001	Central Heating (household installed)	Large equipment	Large household appliances
0002	Photovoltaic Panels (incl. inverters)	Large equipment	Consumer equipment
0101	Professional Heating & Ventilation (excl. cooling equipment)	Large equipment	Large household appliances
0102	Dishwashers	Large equipment	Large household appliances
0103	Kitchen equipment (e.g. large furnaces, ovens, cooking equipment)	Large equipment	Large household appliances
0104	Washing Machines (incl. combined dryers)	Large equipment	Large household appliances
0105	Dryers (wash dryers, centrifuges)	Large equipment	Large household appliances
0106	Household Heating & Ventilation (e.g. hoods, ventilators, space heaters)	Large equipment	Large household appliances
0108	Fridges (incl. combi-fridges)	Temperature exchange equipment	Large household appliances
0109	Freezers	Temperature exchange equipment	Large household appliances
0111	Air Conditioners (household installed and portable)	Temperature exchange equipment	Large household appliances
0112	Other cooling equipment (e.g. dehumidifiers, heat pump dryers)	Temperature exchange equipment	Large household appliances
0113	Professional cooling equipment (e.g. large air conditioners, cooling displays)	Temperature exchange equipment	Large household appliances
0114	Microwaves (incl. combined, excl. grills)	Small equipment	Large household appliances
0201	Other small household equipment (e.g. small ventilators, irons, clocks, adapters)	Small equipment	Small household appliances
0202	Equipment for food preparation (e.g. toaster, grills, food processing, frying pans)	Small equipment	Small household appliances
0203	Small household equipment for hot water preparation (e.g. coffee, tea, water cookers)	Small equipment	Small household appliances
0204	Vacuum Cleaners (excl. professional)	Small equipment	Small household appliances
0205	Personal Care equipment (e.g. toothbrushes, hairdryers, razors)	Small equipment	Small household appliances
0301	Small IT equipment (e.g. routers, mice, keyboards, external drives & accessories)	Small IT	IT and telecommunications equipment
0302	Desktop PCs (excl. monitors, accessories)	Small IT	IT and telecommunications equipment
0303	Laptops (incl. tablets)	Screens and monitors	IT and telecommunications equipment
0304	Printers (e.g. scanners, multi -functionals, faxes)	Small IT	IT and telecommunications equipment
0305	Telecommunication equipment (e.g. cordless phones, answering machines)	Small IT	IT and telecommunications equipment
0306	Mobile Phones (incl. smartphones, pagers)	Small IT	IT and telecommunications equipment
0307	Professional IT equipment (e.g. servers, routers, data storage, copiers)	Large equipment	IT and telecommunications equipment
0308	Cathode Ray Tube Monitors	Screens and monitors	IT and telecommunications equipment
0309	Flat Display Panel Monitors (LCD, LED)	Screens and monitors	IT and telecommunications equipment
0401	Small Consumer Electronics (e.g. headphones, remote controls)	Small equipment	Consumer equipment
0402	Portable Audio & Video (e.g. MP3, e-readers, car navigation)	Small equipment	Consumer equipment
0403	Music Instruments, Radio, Hi-Fi (incl. audio sets)	Small equipment	Consumer equipment
0404	Video (e.g. Video recorders, DVD, Blue Ray, set-top boxes) and projectors	Small equipment	Consumer equipment
0405	Speakers	Small equipment	Consumer equipment
0406	Cameras (e.g. camcorders, photo & digital still cameras)	Small equipment	Consumer equipment
0407	Cathode Ray Tube TVs	Screens and monitors	Consumer equipment
0408	Flat Display Panel TVs (LCD, LED, Plasma)	Screens and monitors	Consumer equipment
0501	Small lighting equipment (excl. LED & incandescent)	Small equipment	Lighting equipment
0502	Compact Fluorescent Lamps (incl. retrofit & non-retrofit)	Lamps	Lighting equipment
0503	Straight Tube Fluorescent Lamps	Lamps	Lighting equipment
0504	Special Lamps (e.g. professional mercury, high & low pressure sodium)	Lamps	Lighting equipment
0505	LED Lamps (incl. retrofit LED lamps)	Lamps	Lighting equipment
0506	Household Luminaires (incl. household incandescent fittings & household LED luminaires)	Small equipment	Lighting equipment
0507	Professional Luminaires (offices, public space, industry)	Small equipment	Lighting equipment

UNU KEY	DESCRIPTION	EEE CATEGORY UNDER EU-6	EEE CATEGORY UNDER EU-10
0507	Professional Luminaires (offices, public space, industry)	Small equipment	Lighting equipment
0601	Household Tools (e.g. drills, saws, high pressure cleaners, lawn mowers)	Small equipment	Electrical and electronic tools
0602	Professional Tools (e.g. for welding, soldering, milling)	Large equipment	Electrical and electronic tools
0701	Toys (e.g. car racing sets, electric trains, music toys, biking computers, drones)	Small equipment	Toys
0702	Game Consoles	Small IT	Toys
0703	Leisure equipment (e.g. sports equipment, electric bikes, juke boxes)	Large equipment	Toys
0801	Household medical equipment (e.g. thermometers, blood pressure meters)	Small equipment	Medical devices
0802	Professional medical equipment (e.g. hospital, dentist, diagnostics)	Large equipment	Medical devices
0901	Household Monitoring & Control equipment (alarm, heat, smoke, excl. screens)	Small equipment	Monitoring and control instruments
0902	Professional Monitoring & Control equipment (e.g. laboratory, control panels)	Large equipment	Monitoring and control instruments
1001	Non- cooled Dispensers (e.g. for vending, hot drinks, tickets, money)	Large equipment	Automatic dispensers
1002	Cooled Dispensers (e.g. for vending, cold drinks)	Temperature exchange equipment	Automatic dispensers

D.1 Link between the UNU-KEYS and HS code (only relevant code in the appendix)

UNU-KEY	UNU KEY DESCRIPTION	HS	HS DESCRIPTION
0305	Telecommunication equipment (e.g. (cordless) phones, answering machines)	903040	Instruments and apparatus; specially designed for telecommunications (eg cross-talk meters, gain measuring instruments, distortion factor meters, psophometers)
0306	Mobile Phones (incl. smartphones, pagers)	851712	Telephones for cellular networks or for other wireless networks
0307	Professional IT equipment (e.g. servers, routers, data storage, copiers)	844312	Printing machinery; offset, sheet fed, office type (sheet size not exceeding 22 x 36cm)
0307	Professional IT equipment (e.g. servers, routers, data storage, copiers)	844339	Printing, copying, and facsimile machines; single-function printing, copying or facsimile machines, not capable of connecting to an automatic data processing machine or to a network
0307	Professional IT equipment (e.g. servers, routers, data storage, copiers)	847050	Cash registers
0307	Professional IT equipment (e.g. servers, routers, data storage, copiers)	847090	Postage-franking machines, ticket-issuing machines which print tickets
0307	Professional IT equipment (e.g. servers, routers, data storage, copiers)	847210	Duplicating machines

Appendix E: temporal disaggregation of the dataset using the tempdisagg package in R.

```r
library(tempdisagg)

options(OutDec = ",")

temp <- (average.6.categories.quarter$EU6PV_1)
temp <- ts(temp, start = 1992, end = 2017)
quarter.temp <- td(temp ~ 1, conversion = "last", to = "quarterly", method = "denton-cholette")
predict(quarter.temp)
```

```
9:1    (Top Level)                                                        R Script
Console   Terminal   Jobs
R 4.1.3 · ~/
> options(OutDec = ",")
> temp <- (average.6.categories.quarter$EU6PV_1)
> temp <- ts(temp, start = 1992, end = 2017)
> quarter.temp <- td(temp ~ 1, conversion = "last", to = "quarterly", method = "denton-cholette")
> predict(quarter.temp)
          Qtr1      Qtr2      Qtr3      Qtr4
1992 0,6597248 0,6597248 0,6597248 0,6597248
1993 0,6815671 0,7034094 0,7252517 0,7470940
1994 0,7693866 0,7916792 0,8139719 0,8362645
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