

Forecasting the European WEEE Collection Rate in Alignment with the SDGs: An Integrated Predictive Framework

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ABSTRACT

The management of Waste Electrical and Electronic Equipment (WEEE) remains a critical sustainability challenge across the European Union (EU). Although the WEEE Directive 2012/19/EU predates the United Nations Sustainable Development Goals (SDGs), its progressively stricter collection targets, from 45% to 65%, are closely aligned with global objectives on sustainable production and consumption. This study develops an integrated predictive framework to forecast the EU27 WEEE Collection Rate (CR) from 2022 to 2030. The framework draws on four modeling families: Statistical methods, Machine Learning (ML) algorithms, Deep Learning (DL) architectures, and selected Hybrid configurations. Data for “Waste Collected” (COL) and “Products Put on the Market” (MKT) were obtained from Eurostat, with missing values imputed through linear interpolation validated against external socioeconomic indicators. Among all models tested, Lasso and Ridge Regression achieved the most accurate forecasts for the COL and MKT datasets, respectively. Although a Hybrid model was implemented to address non-linear residual patterns, it did not outperform the standalone Lasso model, which was retained for CR estimation. The resulting forecasts reveal a consistent downward trend in the Collection Rate, remaining below the 65% target throughout the forecast horizon. This shortfall is primarily driven by an accelerating volume of EEE placed on the market that is not matched by proportional increases in WEEE collection. The findings highlight systemic gaps in current collection mechanisms and underscore the need for enhanced policy interventions. The proposed framework offers a replicable and empirically validated tool to support evidence-based planning and regulatory monitoring in alignment with EU environmental policy and the Sustainable Development Goals.

1. Introduction

1.1 Background and Legislative Framework

The rapid growth in WEEE generation presents major environmental and public health challenges globally. In the European Union, the regulatory response is anchored in Directive 2002/96/EC, later recast as Directive 2012/19/EU, which introduced binding targets to improve e-waste collection, recycling, and recovery (European Parliament and Council, 2002, 2012). Driven by the accelerating consumption of Electrical and Electronic Equipment (EEE) and shortened product life cycles, WEEE has become one of the fastest-growing waste streams worldwide (Balde *et al.*, 2017).

The 2012 Directive set progressive collection targets, beginning at 45% of the average weight of EEE placed on the market in the previous three years (by 2016), and increasing to 65% or 85% of WEEE generated (by 2019) (European Parliament and Council, 2012; European Commission: Eurostat, 2023). These targets reinforced Extended Producer Responsibility (EPR) and harmonized data obligations across member states.

Supporting legislation has further refined the framework, including Commission Regulation (EU) 2017/699, which standardized collection rate calculations, and Decision (EU) 2019/2193, which established common data verification protocols (European Commission, 2017, 2019). More recently, Recommendation (EU) 2023/2585 addressed persistent shortfalls in small electronic returns by encouraging public awareness, infrastructure expansion, and accessible collection schemes (European Commission, 2023).

Within this regulatory context, the Collection Rate (CR) remains the core performance metric for measuring compliance and policy effectiveness. Achieving EU collection targets also contributes meaningfully to the broader objectives of the Sustainable Development Goals (SDGs) (United Nations, 2015), underscoring the importance of WEEE policy in global sustainability efforts.

Despite these policy advancements, substantial variation persists across EU member states, particularly regarding the under-collection of small consumer devices such as mobile phones and laptops. According to the Global E-Waste Monitor 2020, only 22.3% of global e-waste is formally collected and recycled (Forti *et al.*, 2020), highlighting systemic limitations in both global and European collection infrastructures.

1.2 WEEE Directives and SDGs

The WEEE Directives exhibit strong alignment with the Sustainable Development Goals (SDGs), particularly SDG 12 on Responsible Consumption and Production. They directly support Target 12.5, which aims to reduce waste generation through prevention, reduction, recycling, and reuse (United Nations, 2015). The Directives also contribute to SDG 3 by mitigating health risks from hazardous materials, SDG 8 via formal recycling sectors and green job creation, SDG 11 by supporting sustainable urban waste infrastructure, and SDG 13 through reduced emissions from improper waste handling.

A growing body of research confirms this alignment. For example, Gavrilescu *et al.* (2021) introduced the SUSTWEEE framework, which evaluates WEEE systems based on environmental and socio-economic indicators. Other studies have linked EU Directives to sustainability performance and reuse practices (Cole *et al.*, 2019; Santos and Jacobi, 2022; Ghulam and Abushammala, 2023; McMahon, Uchendu and Fitzpatrick, 2023), while Sepre *et al.* (2025) and Grandhi *et al.* (2024) positioned the EU model as a global benchmark for SDG-oriented e-waste policy.

The Sustainable Development in the European Union Reports (European Commission: Eurostat, 2021, 2022, 2023, 2024, 2025) reaffirm WEEE policy's role in achieving SDG 12, emphasizing the importance of ongoing updates to enhance recycling performance. Additionally, the European Committee of the Regions (2022) calls for better SDG integration in national recovery strategies, identifying implementation gaps and best practices. This reinforces the importance of aligning WEEE governance with broader policy tools such as the Recovery and Resilience Facility (RRF) to meet the EU's 2030 Agenda targets. Overall, the EU's WEEE regulatory framework reflects a comprehensive commitment to the SDGs, advancing circularity, waste reduction, and environmental policy integration.

1.3 Review of Existing Forecasting Models and Research Gap

While the WEEE Directives have advanced sustainable waste management practices across Europe, no studies to date have provided forward-looking forecasts of the legally binding Collection Rate (CR) at the EU level. Most existing research instead focuses on retrospective policy evaluations or behavioral determinants (Boubellouta and Kusch-Brandt, 2023), leaving a methodological gap in predictive modeling aligned with regulatory targets.

Although no peer-reviewed research has specifically forecasted CR across the EU, relevant forecasting efforts exist within the broader e-waste domain. In Europe, Wang *et al.* (2013) used ARIMA and multivariate input-output modeling to estimate national e-waste quantities, and Petridis *et al.* (2015) forecasted obsolete computer waste across regional systems. Outside Europe, studies have applied ARIMA (Bagwan, 2024), growth models (Fraige, Al-Khatib and Al-Shaweesh, 2023), lifespan-based simulations (Araújo *et al.*, 2012), and ESG frameworks (Duman and Kongar, 2023) to anticipate WEEE flows at regional or global scales.

In parallel, advanced and hybrid techniques have emerged. Mohsin *et al.* (2022) combined Holt-Winters with Support Vector Regression (SVR) to capture seasonality. In a related development, Chaine *et al.* (2025) applied Random Forests for WEEE plastics classification. Deep Learning applications include Multi-time Scale Attention Network for reverse logistics (Zhang *et al.*, 2023) and improved Grey Models (Xiao and Wang, 2022). Hybrid ML-statistical models have been piloted in Taiwan and Vietnam (Guo and Zhong, 2021).

While previous efforts have addressed WEEE generation or recycling in national contexts, none have provided an EU-wide, multi-model forecast of the legally binding Collection Rate (CR). This represents a significant research gap given the Directive's policy requirements and SDG relevance. Addressing this gap is central to enabling evidence-based planning and anticipating future compliance trajectories (Andreopoulou, Koliouka and Zopounidis, 2020).

1.4 Research Objective and Innovation

In response to the previously identified gap, this study develops a policy-relevant, multi-model forecasting framework for the WEEE Collection Rate across the European Union from 2022 to 2030. Unlike prior research focused on e-waste generation or recycling volumes, this study targets CR directly, a legally binding indicator under the WEEE Directive that remains largely underexplored in predictive modeling.

The research follows two main objectives: First, to construct and evaluate forecasting models across four methodological categories (Statistical, Machine Learning, Deep Learning, a Hybrid approach) and second, to assess whether projected CR values align with the EU's targets and sustainability goals. By offering a comparative evaluation of diverse modeling strategies for EU-wide CR prediction, the study fills a critical methodological void. The resulting forecasts provide a scientific basis for compliance monitoring and contribute to the strategic planning of WEEE governance in support of the SDGs.

2. Methodology

2.1 Data Preprocessing

This study utilizes annual time series data from 2005 to 2021. It focuses on two key indicators: Waste Collected (COL) and Products Put on the Market (MKT). Both are classified under official Eurostat waste operations and are reported for the 27 Member States of the European Union (EU) in metric tons (Eurostat, 2022c).

The selected waste category corresponds to "Waste arising only from separate collection of EEE (6 categories methodology defined in WEEE Directive)" (Eurostat, 2022c). This aggregates data from the six product categories outlined in Annex III of Directive 2012/19/EU. The category reflects only the quantities of WEEE collected through official separate collection schemes. The aggregated values are fully consistent with the sum of the six subcategories reported for each waste management operation, country, and year, in line with Eurostat's methodological framework.

Notably, missing values were present in several countries and in the EU27 aggregate row. To address these gaps, a linear interpolation technique was applied at the country level, followed by the aggregation of corrected country-level values to reconstruct the EU27 dataset. This approach ensured continuity and avoided artificial volatility often introduced by Polynomial Regression or mean substitution (Buuren, 2018; Little and Rubin, 2019). A total of seventy (70) missing values (15.25%) were imputed across the 459 country-year entries. The results were validated through consistency checks using external socioeconomic indicators, including GDP, population, household consumption, and trade turnover (Eurostat, 2024a, 2022a, 2025b, 2022b).

2.2 Exploratory Data Analysis (EDA)

Exploratory Data Analysis (EDA) was employed as a preparatory step to better understand the statistical and temporal characteristics of the datasets prior to model development. This phase included the use of graphical techniques, summary statistics, and correlation analysis to detect patterns, trends, and potential anomalies (Tukey, 1977). Emphasis was placed on identifying structural properties relevant to time-series modelling, such as trends, stationarity, and autocorrelation. These characteristics directly informed decisions related to differencing, model family selection, and the separation of COL and MKT forecasting pipelines.

2.3 Model Selection

Forecasting was approached using four distinct methodological classes: Statistical models, ML, DL, and a Hybrid approach combining both linear and nonlinear strategies. This multi-model approach allows for a robust comparison of forecasting performance across fundamentally different paradigms.

Statistical models, including ARIMA and Holt's Linear Trend model, were selected for their ability to model time series with linear temporal structure. ARIMA captures both autoregressive and moving average components with differencing, making it well-suited for non-stationary series. Holt's method serves as a benchmark for trend-based forecasting and is effective when seasonality is absent (Holt, 2004; Hyndman and Athanasopoulos, 2018).

The ML models applied in this study include the linear methods Linear Regression, Lasso, and Ridge Regression, as well as the non-linear techniques Support Vector Regression (SVR), Random Forest Regression (RFR), and Gradient Boosting Machines (GBM). These models are commonly used for their ability to regularize model complexity and capture non-linear relationships through tree-based or kernel-based learning strategies (Goodfellow, Bengio and Courville, 2016; Brownlee, 2018).

Deep learning models, including Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM) networks, and Gated Recurrent Units (GRU), were implemented to capture non-linear temporal dependencies inherent in the data (Hochreiter and Schmidhuber, 1997; Gers, Schmidhuber and Cummins, 2000; Cho *et al.*, 2014; LeCun, Bengio and Hinton, 2015; Goodfellow, Bengio and Courville, 2016). Additionally, a hybrid model combining Lasso Regression and RNN (Lasso-RNN) was developed to enhance predictive performance through the integration of ML models and DL techniques (Curbelo, Delgado-Gómez and Carreras, 2024).

2.4 Forecasting Procedure, Collection Rate Calculation, and Evaluation Metrics

The forecasting procedure involved training each model on historical data spanning from 2005 to 2021 and subsequently predicting the Collection Rate from 2022 to 2030. Models were trained separately for the COL and MKT datasets. The CR is calculated as the ratio of the quantity of WEEE collected in a given year to the average quantity of EEE placed on the market during the three preceding years (European Parliament and Council, 2012). This calculation aligns with the official EU reporting method and ensures comparability with policy benchmarks. Mathematically, the Collection Rate for year t is expressed as:

$$CR_t(\%) = 100 \cdot \frac{COL_t}{\text{mean}(MKT_{t-1}, MKT_{t-2}, MKT_{t-3})}$$

where: CR_t is the Collection Rate in year t ; COL_t is the quantity of WEEE collected in year t ; MKT_{t-1} , MKT_{t-2} and MKT_{t-3} are the quantities of EEE placed on the market in the three preceding years.

To further demonstrate the models' performance, the published values for the year 2022 from Eurostat, which were 4,988,142 tons for COL and 14,435,717 tons for MKT, were used to assess the percentage difference between the actual and predicted values for that year. These values were not included in the training process, serving as independent benchmarks to evaluate the accuracy of the predictions.

The performance of the predictive models was evaluated using standard metrics commonly applied in time series forecasting, including Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and Coefficient of Determination (R^2). RMSE is particularly effective for evaluating the accuracy of numerical predictions, especially when large errors are undesirable (Chai and Draxler, 2014; Hodson, 2022). MAPE is useful for comparing forecasting methods across different scales and is calculated as the average absolute percentage difference between observed and predicted values (Myttenaere *et al.*, 2016; Hyndman and Athanasopoulos, 2018). The Coefficient of Determination (R^2) assesses the proportion of variance explained by the model, with higher values indicating better fit (Cameron and Windmeijer, 1997; Lewis-Beck and Lewis-Beck, 2015).

3. Results and Discussion

3.1 Handling missing values

This section begins by discussing the methods and results of handling missing values within the COL and MKT time series. Linear interpolation was applied to impute missing values, chosen for its ability to estimate missing points using a smooth and consistent progression derived from existing data trends. This approach ensures that the continuity of the time series is preserved while avoiding unexpected fluctuations or artificial distortions that could compromise the datasets' validity in forecasting (Buuren, 2018; Hyndman and Athanasopoulos, 2018).

The datasets analyzed contain data for individual European countries and an aggregated EU27 row. Since the EU27 row also contained missing values, the imputation process began at the country level. Missing values for individual countries were replaced using linear interpolation, and the corrected country-level data were then aggregated to calculate the EU27 values. This approach ensures that the aggregated regional data accurately reflects the contributions of all member countries, avoiding biases introduced by missing or incomplete data (Little and Rubin, 2019). Additionally, alternative imputation methods were evaluated during this process. Polynomial Regression produced negative values, which were unsuitable for the datasets, while mean substitution resulted in values inconsistent with observed trends, further reinforcing the appropriateness of linear interpolation.

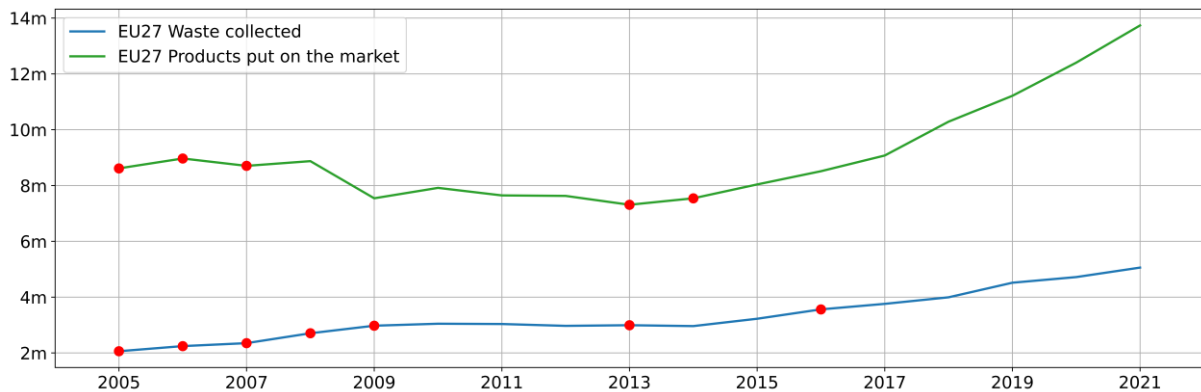


Figure 1. Imputed values (red markers)

In total, seventy (70) missing values were replaced through this process, and the results are summarized in Figure 1. Red markers in the graph denote the imputed values, illustrating the specific points where linear interpolation was applied. The trends observed in the datasets, spanning from 2005 to 2021, demonstrate the method's effectiveness in maintaining the coherence and integrity of the data. The application of linear interpolation and subsequent aggregation ensured a robust foundation for forecasting and compliance assessment. This method has been widely recognized for its computational efficiency and practical application in various domains, as supported by previous studies (Junninen *et al.*, 2004; Chen and Haziza, 2017; Raheem, 2024).

3.2 Validation of Imputed values

To validate the imputed values, four reference datasets were used: “Population on 1 January by age, group and sex” (Eurostat, 2022a), “Gross domestic product (GDP) at market prices” (Eurostat, 2025a), “Household final consumption expenditure by purpose” (Eurostat, 2025b), and “Turnover and volume of sales in wholesale and retail trade” (Eurostat, 2022b). These benchmarks were chosen to ensure that the imputed values for COL and MKT align with key socioeconomic and market-related indicators, thereby enhancing the datasets' robustness and credibility. Correlation analysis and RMSE were employed to assess the consistency between the imputed values and actual economic and demographic trends, providing strong evidence for the reliability of the imputation (Di Zio, Guarnera and Luzi, 2007; Chen and Haziza, 2017).

Correlation analysis reveals strong relationships between the COL dataset and key socioeconomic benchmarks. Specifically, the correlation with Population reaches 0.93, while both GDP and Household Final Consumption Expenditure exhibit correlations of 0.96. These results confirm that the imputed values for waste collected align closely with established demographic and economic trends. Similarly, the MKT dataset shows a correlation of 0.82 with Turnover and Volume of Sales in Wholesale and Retail Trade, and 0.89 with Household Final Consumption Expenditure, highlighting the connection between electronic product flows and consumer activity. Its correlation with GDP, measured at 0.74, indicates a meaningful relationship between market input and overall economic activity, despite being less pronounced than other benchmarks.

The RMSE results complement the correlation findings by quantifying the absolute deviation between the imputed values and benchmark indicators. For the COL dataset, the RMSE is calculated at 0.09 when compared to GDP and 0.11 against Household Final Consumption Expenditure, indicating a very close alignment with real-world trends. For the MKT dataset, the RMSE values remain within acceptable bounds, with 0.14 for Household Final Consumption Expenditure and 0.21 for Turnover and Sales. These low to moderate errors confirm that the imputed time series preserve the underlying patterns of the observed data and do not introduce artificial irregularities that could compromise subsequent analyses or policy interpretation.

Employing multiple benchmarks for validation adheres to the principle of “multiply robust estimation”, which is crucial for ensuring reliable imputation, especially in time series analyses impacted by regulatory and economic factors (Chen and Haziza, 2017). This comprehensive validation strategy ensures that the datasets are robust, accurate, and suitable for informing policy-making and regulatory decisions. Successful validation confirms that the imputation method preserves temporal coherence and maintains consistent relationships between key indicators. This is essential for supporting reliable forecasting and informed policy evaluation, particularly within the framework of the WEEE Directive and the broader sustainability goals (Harel and Zhou, 2007).

The analysis of the two datasets, COL and MKT, provides further insights into the evolution of waste collection and market trends over the observation period from 2005 to 2021. Descriptive statistics, trend analysis, stationarity assessment, and normality tests were performed to understand the underlying patterns and statistical characteristics of both datasets. These analyses enabled a comprehensive evaluation of the observed trends within their legislative context.

3.3 Descriptive statistics

The descriptive statistics for the COL and MKT datasets are presented as follows. The mean value for COL is approximately 3,304,640 metric tons, with a standard deviation of 858,973 metric tons, reflecting moderate variability over the observation period. The minimum observed value is 2,061,209 metric tons, while the maximum is 5,057,977 metric tons, indicating a significant range in waste collection volumes. The interquartile range (IQR), spanning from 2,962,210 to 3,759,118 metric tons, suggests that most values fall within this range, reflecting relatively consistent waste collection trends.

In contrast, MKT exhibits greater variability, with a mean of 9,059,032 metric tons and a standard deviation of 1,836,094 metric tons. The minimum value recorded is 7,309,899 metric tons, while the maximum is 13,735,968 metric tons, indicating a notable increase in market activity throughout the observation period. The IQR, ranging from 7,644,999 to 9,074,687 metric tons, highlights substantial dispersion, which aligns with the dynamic nature of electronic product consumption. Factors such as technological advancements, consumer preferences, and economic fluctuations likely contribute to this variability.

3.4 Trend analysis

Figure 2 illustrates the trends for COL and MKT from 2005 to 2021, with key legislative milestones represented by vertical dashed lines. The red dashed line denotes the 2012 WEEE Directive Recast, while the orange dashed line indicates the 2016 Collection Target Change. Both events have significantly shaped the trends observed in these datasets. The analysis highlights the influence of

legislative actions, economic recovery, and technological advancements, alongside broader societal and global factors.

The COL dataset demonstrates a steady upward trajectory throughout the period. A particular notable increase follows the 2012 WEEE Directive Recast, which introduced stricter collection targets, expanded the scope of covered equipment and enhanced producer responsibility frameworks. Quantitatively, waste collected in the EU27 increased from 3.0 million tons in 2012 to 4.9 million tons in 2021, marking a 63.3% growth over the period (Eurostat, 2024a). These policy changes prompted member states to invest in better collection systems and infrastructure, contributing to the observed growth. The upward trend aligns with the EU's sustainability goals, particularly resource recovery and the promotion of a circular economy (European Commission, 2015).

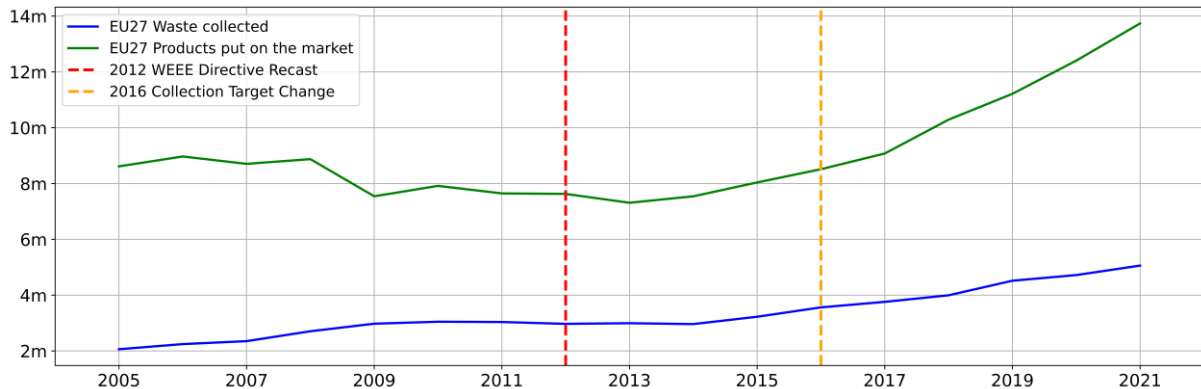


Figure 2. Impact of WEEE Policy Milestones on EU27 COL and MKT trends

The MKT dataset shows a consistent growth trend, particularly after 2016. This increase reflects the expanding market for EEE, driven by rising consumer demand and rapid technological advancements (European Commission, 2020a; Lopez and Soltani, 2023). Between 2012 and 2021, the amount of EEE placed on the market increased from 7.6 million tons to 13.0 million tons, representing a 71.1% growth (Eurostat, 2024b). This growth also aligns with Europe's economic recovery following the 2008 financial crisis, which had caused a temporary slowdown in EEE production and consumption (European Commission, 2009). During the crisis, reduced disposable income and economic uncertainty delayed consumer purchases, with EEE production slowing down between 2008 and 2011 (European Central Bank, 2014). However, from 2012 onward, GDP and household consumption expenditure increased steadily, growing by 1.5% to 2.2% annually during the period 2014-2019. As a result, the volume of EEE placed on the market also began to rise, reinforcing the link between economic conditions and consumer behaviour (Eurostat, 2024a, 2024b).

Legislative milestones such as the WEEE Directive recast and the 2016 Collection Target change remain pivotal in shaping these trends. However, broader economic and societal dynamics also play a significant role. For example, the EU's Digital Agenda for Europe, launched in 2010, accelerated digitalization and integration of electronic technologies across sectors, contributing to the observed increase in EEE placed on the market (European Commission, 2010). Simultaneously, the successful implementation of extended producer responsibility (EPR) schemes encouraged proper recycling and disposal of outdated equipment, with WEEE collection increasing by 63.3% between 2012 and 2021 (Balde *et al.*, 2017; Eurostat, 2024b).

More recently, the COVID-19 pandemic introduced a dual effect that further influenced both market expansion and collection dynamics. On one hand, supply chain disruptions temporarily slowed the production and sale of electronic goods. On the other hand, the shift to remote work, online education, and digital communication increased demand for devices such as laptops and tablets, offsetting potential declines in the market (Forti *et al.*, 2020). Meanwhile, logistical challenges, such as reduced operational capacity at recycling facilities and movement restrictions, likely hindered waste collection efforts, contributing to a plateau in the upward trajectory observed in previous years.

In parallel with these developments, the adoption of the United Nations Sustainable Development Goals (SDGs) in 2015 further reinforced the EU's commitment to improving e-waste management through stricter WEEE collection targets (United Nations, 2015). While the decision to revise these targets predates the SDGs, the alignment of EU policies with global sustainability objectives reflects a broader commitment to promoting responsible e-waste management and environmental protection.

A final methodological note concerns the decision not to conduct seasonal decomposition. This choice is justified by the absence of recurring seasonal patterns in the datasets, as visual inspection revealed no clear peaks or troughs suggestive of cyclicity. Instead, the data reflects structural trends shaped by long-term growth and broad political, legislative, and economic developments. Notably, the 2012 WEEE Directive Recast and the 2016 revision of collection targets mark decisive policy shifts that influenced both waste collection and market dynamics. These observations reinforce the importance of focusing on structural and regulatory drivers, rather than attempting to model seasonal effects that are not empirically present.

3.5 Stationarity assessment (ADF Test)

To determine whether the datasets are stationary, the Augmented Dickey-Fuller (ADF) test was performed on both time series (Dickey and Fuller, 1979). Stationarity is essential for further predictive modelling, as many time series models assume constant statistical properties over time.

For the COL series, the ADF test statistic was 6.6230 ($p = 1.000$), providing clear evidence of non-stationarity. Similarly, the MKT series yielded an ADF statistic of -2.4900 with a p -value of 0.1179, which also exceeds the 0.05 significance threshold. In both cases, the null hypothesis of a unit root cannot be rejected, confirming that neither time series is stationary. This non-stationary behaviour is likely driven by long-term trends and external structural factors, which must be accounted for during model development.

3.6 Predictive Modelling Framework

This section develops forecasting models for the COL and MKT time series. The analysis is structured as a comparative modelling framework, progressing from baseline benchmarks to statistical, machine learning, deep learning, and hybrid specifications. Model assessment follows a consistent evaluation protocol that prioritizes out-of-sample performance, while residual-based checks are used to support the interpretation of fitted specifications and to identify remaining structure that may justify more flexible modelling strategies. The following subsections present the predictive models examined in this study, beginning with baseline models that establish reference performance levels for transparent benchmarking.

Baseline models

Baseline models provide a transparent benchmark against which the incremental value of more advanced forecasting approaches can be assessed. Their appeal lies in their simplicity and minimal assumptions, making them suitable for preliminary performance comparisons in time series forecasting (Armstrong, 2001; Makridakis, Spiliotis and Assimakopoulos, 2018).

In this study, three (3) baseline models were implemented, namely Naive, Mean, and Simple Exponential Smoothing (SES). A Moving Average benchmark was considered but excluded due to its functional overlap with SES and limited additional empirical value (Gardner, 1985; Makridakis, Spiliotis and Assimakopoulos, 2018). Naive extrapolates the most recent observation and is appropriate under persistence (Wheelwright, Makridakis and Hyndman, 1998), Mean uses the historical average and is generally suitable only for stationary and trend-free series (Makridakis, Spiliotis and Assimakopoulos, 2018), while SES applies exponentially declining weights that emphasize recent values and allow smooth adaptation to gradual change (Gardner, 1985).

The comparative evaluation reveals clear performance differences when the series exhibits trend dynamics. For the COL dataset, the Naive and SES models performed similarly, with MAPE values of 15.99% and 16.02%, respectively, whereas the Mean model underperformed substantially (MAPE 37.07%). This gap is consistent with the limited capacity of mean-based benchmarks to represent non-

stationary behavior and directional change. A secondary validation based on 2022 forecast errors supports the same ranking. For COL, the Naive and SES models yielded deviations of -19.94% and -19.96%, respectively, compared with -40.02% for the Mean baseline, while for MKT the Mean model also exhibited a pronounced deviation (-42.28%). Collectively, these outcomes indicate that simple average-based forecasts are particularly sensitive to temporal evolution in expanding market conditions.

Overall, the baseline results establish a conservative performance floor against which subsequent statistical, ML, DL, and hybrid models can be evaluated. The observed limitations in baseline accuracy therefore motivate the transition to more flexible forecasting architectures capable of capturing the structural complexity required for long-term WEEE management assessments.

Statistical Models

Following the baseline evaluation, two statistical models were implemented to capture linear temporal dependencies in the datasets, namely the AutoRegressive Integrated Moving Average (ARIMA) model and Holt's Linear Trend model. Both are suited for univariate time series forecasting and serve as critical benchmarks prior to introducing machine learning approaches.

ARIMA Model

The AutoRegressive Integrated Moving Average (ARIMA) model was employed to capture linear temporal dynamics in the COL and MKT time series. This class of models is particularly well-suited for analyzing non-stationary data, as it incorporates autoregressive (AR) and moving average (MA) terms alongside differencing to achieve stationarity. Its flexibility and interpretability have made ARIMA a standard approach in environmental and policy-oriented forecasting applications (Box, Jenkins and Reinsel, 2008).

Stationarity Analysis

Stationarity was first assessed using the Augmented Dickey-Fuller (ADF) test (see Section 3.5). The test results confirmed that both datasets were non-stationary in their original and first-differenced forms. Specifically, for the COL series, the ADF statistics after first differencing was 1.7808 ($p = 0.9983$), indicating strong persistence. After applying a second differencing, the statistics dropped to -3.4493 ($p = 0.0094$), enabling rejection of the unit root null hypothesis at the 1% level. Similarly, the MKT series exhibited an ADF statistic of -1.1601 ($p = 0.6905$) after first differencing, which improved to -7.6374 ($p < 0.0001$) after second differencing, confirming stationarity.

Model Identification and Order Selection

The AutoCorrelation Function (ACF) and Partial AutoCorrelation Function (PACF) plots (Box et al., 2008) for the second-differenced series (Figure 3) were utilized to determine the optimal ARIMA model orders. These plots provide insights into the underlying autoregressive (AR) and moving average (MA) components needed to model the series effectively.

For the COL dataset, the absence of statistically significant spikes in both plots initially suggested that ARIMA (0,2,0) might suffice, implying that differencing alone could remove temporal dependency. However, empirical testing revealed that a slightly more complex specification, ARIMA (1,2,1), significantly reduced forecast errors and improved residual behaviour.

In contrast, the MKT dataset displayed more pronounced temporal patterns. The ACF revealed a strong negative spike at lag 1 and a positive spike at lag 2, consistent with an MA (1) structure. Simultaneously, the PACF exhibited a significant negative spike at lag 1, indicating the presence of an AR (1) process. These features collectively supported the adoption of an ARIMA (1,2,1) model for MKT.

Alternative specifications, including ARIMA (1,2,3) and ARIMA (1,2,4), were evaluated for both series. However, these models produced higher values in Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), suggesting an unfavourable complexity-performance tradeoff. For instance, the ARIMA (1,2,1) model for COL yielded an AIC of 408.4 and BIC of 410.5, outperforming more complex configurations that introduced marginal gains in fit at the cost of interpretability and parsimony.

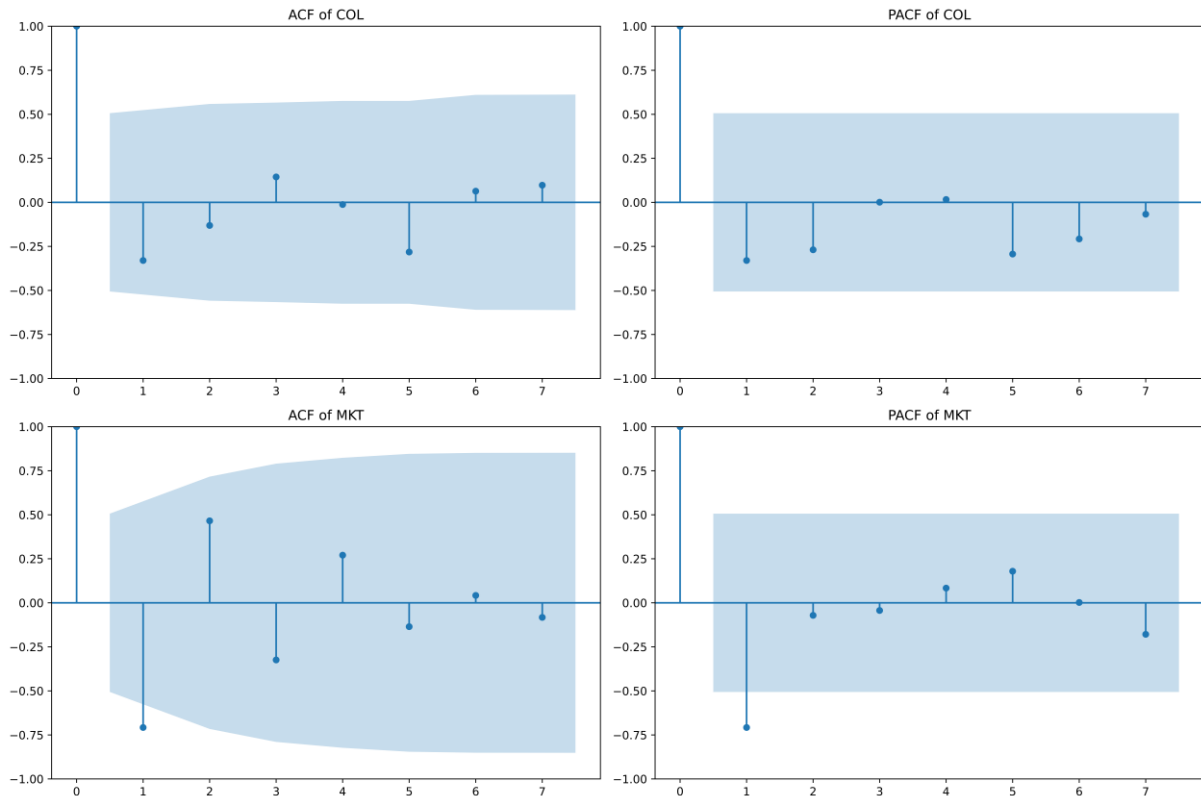


Figure 3. ACF and PACF of the Second-Differenced COL and MKT Series

Parameter Estimates and Residual Diagnostics

When applied to the COL dataset, the fitted ARIMA (1,2,1) model reported an AR (1) coefficient of 0.6987 ($p = 0.003$), indicating moderate temporal persistence, while the MA (1) coefficient of -0.9859 was not statistically significant ($p = 0.146$). Despite this, the model passed residual diagnostics: the Ljung-Box test (Ljung and Box, 1978) statistic at lag 1 was 1.00 ($p = 0.32$), indicating no significant autocorrelation, and the Jarque-Bera (Jarque and Bera, 1987) test confirmed residual normality ($p = 0.58$).

In the case of the MKT series, both the AR (1) and MA (1) parameters were statistically significant ($p < 0.001$), with values of -0.8591 and 0.9611, respectively. The residuals again satisfied the diagnostic checks, with a Ljung-Box p-value of 0.20 and a Jarque-Bera p-value of 0.94, supporting the model's validity.

Forecast accuracy was assessed using a rolling-window cross-validation framework (Bergmeir and Benítez, 2012). For the COL dataset, the ARIMA (1,2,1) model achieved a MAPE of 4.35%, RMSE of 231,241.54, and R^2 of 0.42. Performance was notably stronger for the MKT series, with a MAPE of 2.60%, RMSE of 309,262.76, and R^2 of 0.87. These results indicate the model's effectiveness in capturing the underlying linear structures, particularly in the MKT series.

When compared to the actual values for 2022, the ARIMA model recorded percentage differences of 7.71% for COL and 5.35% for MKT. This further supports its reliability in short-term forecasting, particularly under conditions of strong trend persistence and structural regularity.

Holt's Linear Trend Model

Holt's Linear Trend model, a special case of the Holt-Winters Exponential Smoothing (HWES) family, was applied as an alternative statistical benchmark to ARIMA. Unlike ARIMA, which models time series through autoregressive and moving average structures, Holt's method directly estimates the level and trend components via exponential smoothing. This makes it particularly suitable for non-seasonal time series exhibiting a persistent trend (Holt, 2004; Yapar *et al.*, 2018).

The method's simplicity and computational efficiency allow it to serve as a practical forecasting tool, especially in applications where transparency and interpretability are valued (Ariffin *et al.*, 2024). Given the absence of pronounced seasonal cycles in the COL and MKT datasets, Holt's Linear Trend model was deemed an appropriate candidate for capturing long-term directional movement. Its inclusion provides a useful point of comparison to ARIMA, especially in evaluating performance under constrained model structures (Hyndman and Athanasopoulos, 2018).

Model evaluation was conducted using a train-test split and out-of-sample validation (Tashman, 2000). The COL model produced a MAPE of 12.26%, an RMSE of 608,941, and an R^2 value of -6.42, indicating that the model failed to capture the structural dynamics of the waste collection series. This result points to a significant limitation in its ability to adapt to the accelerating growth observed in the post-2012 period. For the MKT dataset, performance was comparatively better, with a MAPE of 5.26%, RMSE of 752,869, and an R^2 of 0.46. While the model was able to approximate the overall upward trend in EEE placed on the market, the residual variance suggests a lack of responsiveness to structural accelerations.

Short-term forecasting accuracy was further assessed using 2022 projections. For COL, the model underestimated the actual value by 18.12%, predicting 4,084,300 tons versus the observed 4,988,142. Similarly, for MKT, the predicted value was 10,911,460 tons, falling short of the actual 14,435,717 by 24.41%. These underestimations confirm the model's limited adaptability to non-linear or rapidly evolving trends, particularly in the more volatile MKT series.

Statistical Model selection

The evaluation of ARIMA and Holt's Linear Trend model revealed that ARIMA (1,2,1) provided consistently superior results across both datasets. It achieved lower error metrics and better R^2 values, while also demonstrating stronger alignment with the 2022 observed values. In contrast, Holt's model underperformed, particularly for COL, where it recorded a negative R^2 and significant underestimation. Due to its superior predictive accuracy and more favourable diagnostic properties, ARIMA (1,2,1) is selected as the primary statistical benchmark for subsequent comparisons with ML, DL, and Hybrid models.

Machine Learning models (ML)

This study investigated a range of machine learning models, including Linear Regression, Lasso Regression, Ridge Regression, Support Vector Regression (SVR), Random Forest Regression (RFR), and Gradient Boosting Machines (GBM). These models were selected for their varying capacities to capture both linear and non-linear relationships in time series data. To ensure robust performance, each model was trained using time-aware strategies that preserved the temporal structure of the data. In addition, feature engineering techniques were applied to incorporate historical dependencies and enhance predictive accuracy.

Linear, Lasso and Ridge Regression Models

The first group of ML models includes standard Linear Regression, along with its regularized counterparts, Lasso and Ridge Regression. These models were selected for their interpretability and compatibility with engineered features designed to reflect temporal dynamics in the data. Prior to training, the datasets underwent feature engineering to incorporate a linear time trend, rolling means, and lag variables, enabling the models to account for both short- and long-term dependencies. A walk-forward validation strategy was adopted to simulate a realistic forecasting scenario by training on historical data and predicting future values (Wahyuddin *et al.*, 2025).

To ensure comparability across input features and prevent scale-sensitive models from being biased, all predictors were standardized using StandardScaler (Pedregosa *et al.*, 2011). While Linear Regression served as a baseline, Lasso (L1 regularization) and Ridge (L2 regularization) introduced penalties on model complexity to improve generalization and reduce overfitting. Their hyperparameters were tuned via Bayesian optimization using Optuna (Akiba *et al.*, 2019), allowing for an efficient exploration of the regularization space tailored to time series characteristics.

Performance evaluation for the COL dataset revealed that Linear Regression achieved a MAPE of 2.98 %, an RMSE of 166,590.77, and an R^2 of 0.46, indicating moderate explanatory power. Lasso Regression produced a nearly identical result, with an improved MAPE of 2.82%, RMSE of 158,196.36 and R^2 of 0.50. Ridge Regression, however, underperformed with a higher MAPE of 4.17%, an RMSE of 213,103.19, and an R^2 of 0.09, suggesting weaker fit. Forecasting performance for 2022 mirrored these findings: Lasso predicted within 1.14% of the actual value, Linear Regression within -1.27%, while Ridge overestimated significantly by 11.50%.

For the MKT dataset, the models behaved differently. Both Linear and Lasso Regression recorded MAPE values of 7.14% and R^2 scores of -0.01, indicating minimal ability to explain the variance. In contrast, Ridge Regression excelled, with a MAPE of 1.71%, an RMSE of 253,894.85, and a strong R^2 of 0.91. Its 2022 forecast deviated by only 5.08% from the observed value, while Lasso and Linear models overestimated by 26.80% and 25.08%, respectively.

Support Vector, Random Forest and Gradient Boosting Regression Models

The second set of machine learning models includes Support Vector Regression (SVR), Random Forest Regression (RFR), and Gradient Boosting Regression (GBM). These models were designed to capture non-linear relationships and hierarchical interactions that are often overlooked by linear algorithms. While the feature set and data preparation procedures remained consistent with those applied in the previous models, their inclusion here allowed for the evaluation of more flexible approaches. Forecasting was conducted within a time-aware framework to ensure temporal integrity, with validation performed on chronologically held-out data segments.

Hyperparameter optimization was conducted separately for each model using established cross-validation techniques. The SVR model underwent a grid search across kernel types, regularization strength (C), gamma, and epsilon parameters to identify the configuration yielding optimal performance (Pedregosa *et al.*, 2011). Random Forest and Gradient Boosting models were tuned using RandomizedSearchCV (Pedregosa *et al.*, 2011), targeting parameters such as the number of estimators, maximum tree depth, minimum samples per split and per leaf, and subsampling strategies. In each case, TimeSeriesSplit cross-validation was employed to prevent data leakage and improve generalization (Pedregosa *et al.*, 2011).

Performance results for the COL dataset revealed that GBM outperformed the other non-linear models, achieving a MAPE of 15.99% and an RMSE of 802,261.73. Although its R^2 was negative (-11.88), it still produced the most accurate forecast for 2022, with a percentage difference of -19.93%. RFR performed moderately well, with a MAPE of 20.50% and an RMSE of 1,009,922.82, while SVR lagged significantly, showing poor generalization with a MAPE of 36.13%, an RMSE of 1,742,105.32, and an R^2 of -59.74. The large negative R^2 values across all three models suggest difficulty in modelling the linear and trend-dominated behaviour of COL using non-linear methods.

Similar trends were observed for the MKT dataset. GBM again yielded the best results, with a MAPE of 16.82%, an RMSE of 2,397,257.25, and an R^2 of -4.42, outperforming both RFR (MAPE=32.36%, R^2 =-15.73) and SVR (MAPE=35.99%, R^2 =-19.39). While all models struggled to explain variance, likely due to the strong underlying linearity of the MKT series, GBM maintained relatively stable predictions. For 2022, GBM's forecast was closest to the observed value, with a percentage difference of -28.74%, compared to -42.05% for RFR and -45.17% for SVR.

ML Model selection

In the COL dataset, Lasso Regression demonstrated the most balanced forecasting behaviour, achieving high predictive accuracy while maintaining generalizability. The model's forecast for 2022 fell well within the empirical range of the historical series, which spans from just over two (2) to approximately five (5) million metric tons, indicating that it avoided producing extreme or unrealistic outputs. The dataset's standard deviation is approximately 859,000 metric tons, and within this context, the model's prediction errors remained within a range that aligns with the series' natural year-to-year fluctuations. This suggests that Lasso successfully modelled the underlying trend without overfitting to noise or anomalies. The application of L1 regularization was instrumental in this performance, as it

limits model complexity by reducing the magnitude of less influential coefficients, thereby promoting sparsity and enhancing the model's generalization capacity. The stability of Lasso across both in-sample and out-of-sample evaluations reinforces its suitability for forecasting the moderately volatile COL series.

For the MKT dataset, characterized by higher temporal variability and a broader dynamic range, Ridge Regression proved to be the most effective model. Its 2022 forecast slightly exceeded the dataset's historical maximum of approximately 13.7 million metric tons but remained a plausible extension of the observed trend. Given the dataset's standard deviation, over 1.8 million metric tons, this prediction falls within a tolerable deviation that reflects the inherent variability of the series. Importantly, the model preserved consistency across different time horizons, producing forecasts that were both stable and aligned with the overall growth trajectory of the data. Ridge's L2 regularization mechanism further contributed to this outcome by penalizing large coefficient estimates, thereby reducing the risk of overfitting in the presence of multicollinearity or artificial correlations in the data. The model's controlled and interpretable behaviour underpins its effectiveness for forecasting in high-variance, structurally evolving time series like MKT.

Deep Learning Models (DL)

To further enhance forecasting accuracy, this study employed three Deep Learning (DL) architectures: Recurrent Neural Networks (RNN), Long Short-Term Memory networks (LSTM), and Gated Recurrent Units (GRU). These models are designed to capture complex temporal dependencies in sequential data and are well-suited for detecting non-linear patterns and long-range dynamics across time steps.

RNN, LSTM, and GRU Model Architectures

Each architecture was implemented with an enhanced design integrating Deep Neural Network (DNN) components to improve pattern recognition and forecasting performance. Input data were preprocessed through sequence generation and normalization, and engineered features were used to preserve short- and long-term temporal signals. A time-aware cross-validation strategy based on TimeSeriesSplit (Pedregosa *et al.*, 2011) ensured evaluation integrity by maintaining the chronological structure during both training and validation.

The DL architectures shared a common structure: stacked recurrent layers with decreasing unit counts, followed by dense layers. RMSprop was employed as the optimizer, chosen for its capacity to maintain a stable learning rate and manage the non-stationary behaviour of time-series data (Ruder, 2017). To minimize the risk of overfitting, dropout layers and L2 regularization were incorporated. The hyperparameters, such as the number of recurrent units, dropout rates, learning rates, and regularization coefficients, were fine-tuned for each model. Training efficiency and convergence were supported by early stopping and learning rate adaptation techniques, enabling more refined learning through mechanisms like ReduceLROnPlateau (Abadi *et al.*, 2015; Al-Kababji, Bensaali and Dakua, 2022). All forecasts were rescaled to ensure interpretability on the original data scale.

Performance Evaluation Based on Loss Function Convergence

Figure 4 displays the loss function curves for the RNN model trained on the COL and MKT datasets. Both the training and validation losses show smooth and consistent convergence across epochs, with a progressively narrowing gap between them, indicative of strong generalization and minimal overfitting. The presence of minor plateaus followed by further declines in loss reflects the impact of the adaptive learning rate strategy employed during training, specifically the ReduceLROnPlateau callback. This mechanism allows the model to respond effectively to diminishing improvements by fine-tuning the learning process. Such training behaviour aligns with best practices in deep learning optimization and reinforces the robustness of the model architecture (Al-Kababji, Bensaali and Dakua, 2022).

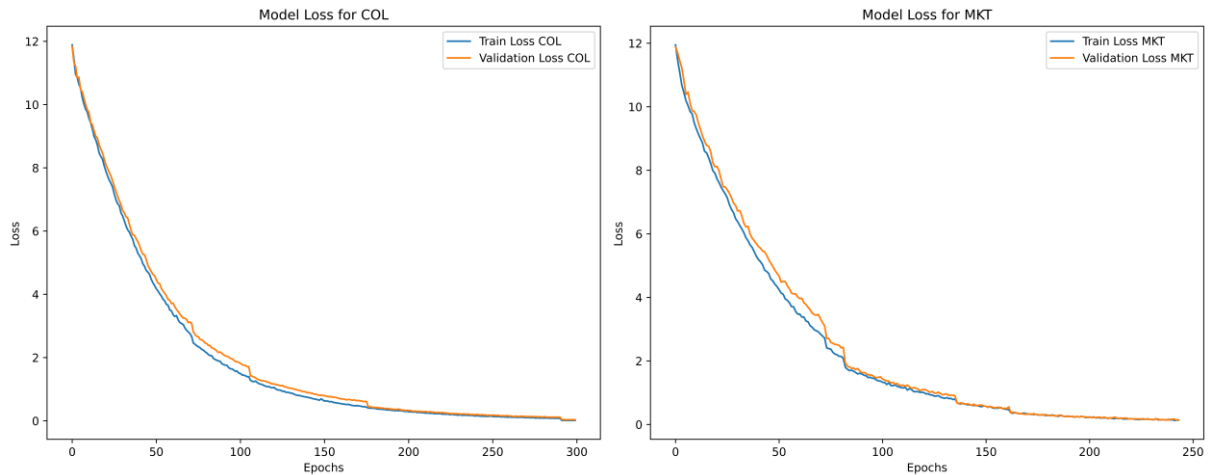


Figure 4. Training and Validation Loss Curves for RNN model on the COL and MKT datasets

The learning dynamics of the LSTM architecture, as depicted in Figure 5, reveal important insights into the model's training behaviour. While the initial epochs show steep reductions in training and validation losses, indicating efficient early learning, the curves begin to diverge after approximately 50 epochs. For the MKT dataset in particular, the widening gap between training and validation losses suggests mild overfitting. Although the use of learning rate schedulers helps recover from local plateaus, the model exhibits reduced generalization capability, especially for complex datasets. In contrast, the COL dataset shows better alignment between training and validation losses, suggesting greater robustness and improved extrapolation capacity.

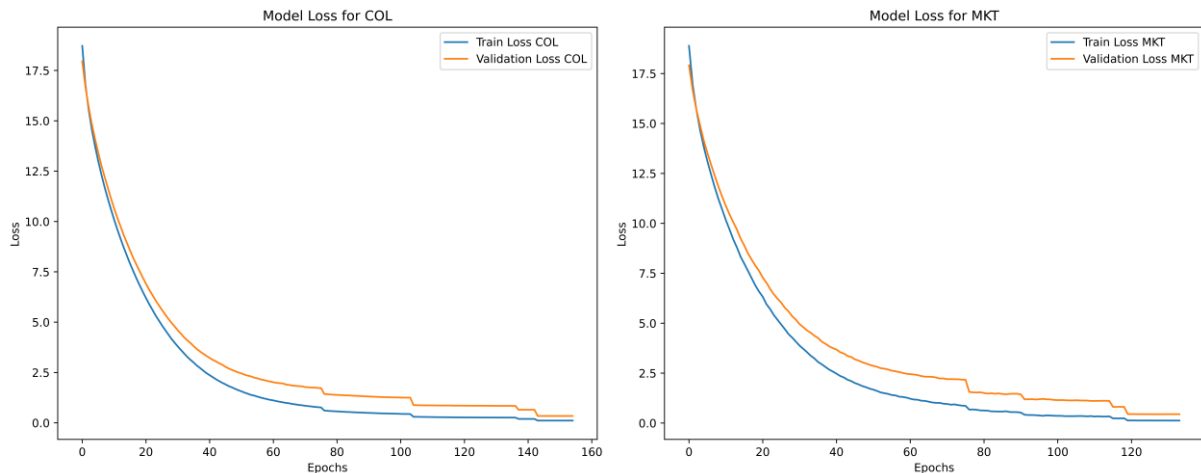


Figure 5. Training and Validation Loss Curves for LSTM model on the COL and MKT datasets

As shown in Figure 6, the GRU architecture also achieves steady declines in both training and validation losses. For the COL dataset, the convergence of the two curves by the final epochs supports the model's generalization ability. However, in the case of the MKT dataset, a persistent gap remains between the two curves, suggesting slight overfitting. Despite this, the GRU still captures key temporal dynamics reasonably well, aided by its simplified gating mechanism that facilitates the learning of both short-term and long-term patterns.

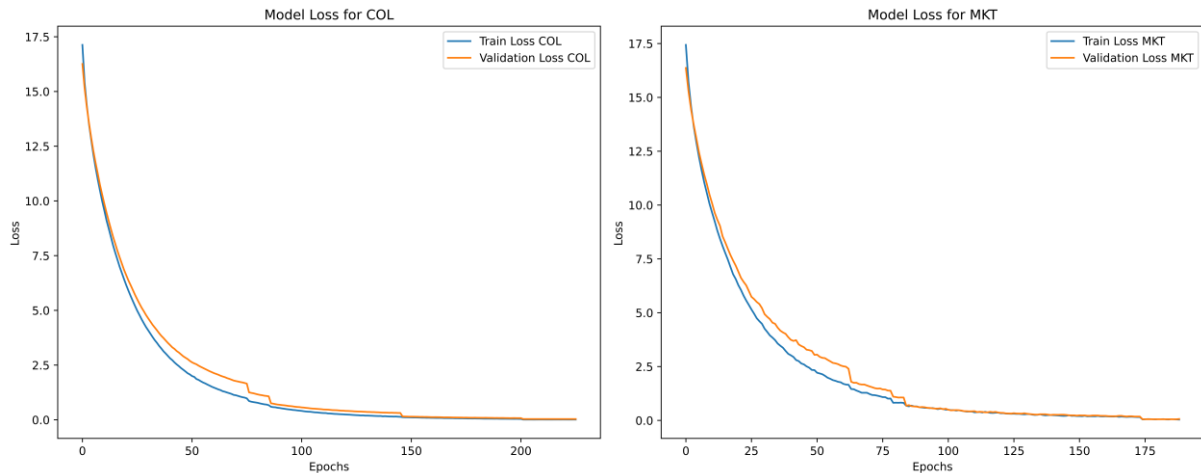


Figure 6. Training and Validation Loss Curves for GRU model on the COL and MKT datasets

DL Model selection

For COL, the RNN provided the most consistent generalization and forecasting stability, achieving a MAPE of 4.12% and an R^2 of 0.82. The LSTM displayed weaker generalization behavior, while the GRU produced comparatively stable forecasts but did not match the RNN's precision and trend fidelity. For MKT, the RNN again yielded the most coherent performance (MAPE 3.40%, R^2 0.86), capturing the overall trajectory and local fluctuations. In contrast, the LSTM showed reduced generalization consistent with its loss-curve divergence, and GRU forecasts tended to flatten over the horizon, limiting representational accuracy. Collectively, these outcomes support selecting the RNN as the most robust DL model for integration within the overall framework.

Hybrid Model

The selection of an optimal forecasting model in data science requires a systematic comparison of different methodologies to determine the most effective approach for a given dataset (Hyndman and Athanasopoulos, 2018; Borchert *et al.*, 2022). The following tables (Table 1 and Table 2) present the models' performance metrics and the percentage differences of 2022 predictions, which serve as a benchmark for further analysis and the development of hybrid models.

The results indicate that among ML models, Lasso Regression achieved the best performance for COL, while Ridge Regression outperformed all other models for MKT. Meanwhile, DL models (RNN, LSTM, GRU) did not consistently surpass the best-performing ML models, suggesting that Neural Networks (NNs) alone may not necessarily provide superior forecasting accuracy. However, RNN exhibited strong predictive capabilities and is structurally suited to capture temporal dependencies, making it a natural complement to Lasso and Ridge Regression in a hybrid framework.

Hybrid models have emerged as a pivotal approach in time series forecasting, seeking to combine the strengths of multiple methodologies to enhance predictive robustness (Zhang, 2003; Khashei and Bijari, 2011). Machine Learning models, such as Lasso and Ridge Regression, are particularly effective at capturing linear dependencies, while NNs are well-suited for learning non-linear relationships (Zhang, Eddy Patuwo and Y. Hu, 1998). This combination has demonstrated effectiveness across various domains, including financial time series forecasting and environmental data analysis, reinforcing its adaptability and applicability. Recent studies have further validated the potential of hybrid models, highlighting how the integration of Lasso (Sun, Huang and Gao, 2012; Xu *et al.*, 2019; Curbelo, Delgado-Gómez and Carreras, 2024) and Ridge (Sonoda, Ishikawa and Ikeda, 2021; Nahiduzzaman *et al.*, 2025) Regression with NNs can enhance forecasting performance by effectively capturing both linear trends and intricate temporal dependencies. However, while hybrid models have demonstrated success in various applications, their effectiveness is not guaranteed and remains dataset-dependent (Xu *et al.*, 2019; Sina *et al.*, 2023). Given the strong performance of Lasso and Ridge Regression, an empirical investigation is required to assess whether integrating an NN into these models can enhance predictive performance.

Table 1. Performance metrics of the models

Models	Waste Collected (COL)			Products put on the Market (MKT)		
	MAPE (%)	RMSE	R ²	MAPE (%)	RMSE	R ²
Naive	15.99	802,340	-11.88	16.81	2,395,997	-4.41
Mean	37.07	1,786,440	-62.87	32.62	4,245,510	-15.98
Simple Exponential Smoothing	16.02	803,472	-11.92	16.86	2,401,486	-4.43
ARIMA	4.35%	231,241.54	0.42	2.60%	309,262.76	0.87
Holt's Linear Trend model	12.26%	608,941.00	-6.42	5.26%	752,869.00	0.46
Lasso Regression	2.82%	158,196.36	0.50	7.14%	1,032,923.31	-0.01
Ridge Regression	4.17%	213,103.19	0.09	1.71%	253,894.85	0.91
Linear Regression	2.98%	166,590.77	0.46	7.14%	1,033,014.05	-0.01
Support Vector Regression	36.13%	1,742,105.32	-59.74	35.99%	4,651,467.32	-19.39
Random Forest Regression	20.50%	1,009,922.82	-19.41	32.36%	4,213,855.37	-15.73
Gradient Boosting Regression	15.99%	802,261.73	-11.88	16.82%	2,397,257.25	-4.42
RNN	4.12%	199,535.05	0.82	3.40%	427,591.70	0.86
LSTM	4.27%	292,531.95	0.74	17.33%	2,202,228.64	-0.07
GRU	5.07%	249,761.58	0.78	15.16%	2,205,860.59	-0.15

Table 2. Percentage deviation between predicted and actual values for 2022

Models	COL - 2022 Actual Value 4,988,142		MKT - 2022 Actual Value 14,435,717	
	Prediction	Deviation (%)	Prediction	Deviation (%)
Naive	3,993,690	-19.94%	10,287,613	-28.74%
Mean	2,991,864	-40.02%	8,332,214	-42.28%
Simple Exponential Smoothing	3,992,512	-19.96%	10,281,534	-28.78%
ARIMA	5,372,938	7.71%	15,207,386	5.35%
Holt's Linear Trend model	4,084,300	-18.12%	10,911,460	-24.41%
Lasso Regression	5,044,847	1.14%	18,303,795	26.80%
Ridge Regression	5,561,800	11.50%	15,169,037	5.08%
Linear Regression	4,922,836	-1.27%	18,055,533	25.08%
Support Vector Regression	3,037,029	-39.13%	7,915,349	-45.17%
Random Forest Regression	3,779,389	-24.23%	8,364,852	-42.05%
Gradient Boosting Regression	3,993,772	-19.93%	10,286,217	-28.74%
RNN	4,774,771	-4.28%	13,051,771	-9.59%
LSTM	6,221,797	24.73%	9,009,396	-37.59%
GRU	4,965,022	-0.46%	8,475,244	-41.29%

Evaluating Residuals: Justification for Hybridization

A crucial step in assessing the viability of hybrid models is to analyze the residuals of the best-performing ML models (Lasso for COL and Ridge for MKT). Residual diagnostics provide insight into whether additional modelling is required, particularly in terms of capturing non-linearity or addressing stationarity issues (Ardalani-Farsa and Zolfaghari, 2011; Goel, Melnyk and Banerjee, 2017; Atesongun and Gulsen, 2024).

Residual Analysis of Lasso Regression for COL dataset

To assess the adequacy of Lasso Regression in modelling the COL dataset, a comprehensive residual diagnostic analysis was conducted. The ACF plot (Figure 7) indicates that most residuals fall within the

95% confidence bands, suggesting that no strong autocorrelation remains, except for a small spike at lag 7, which does not exceed the significance threshold.

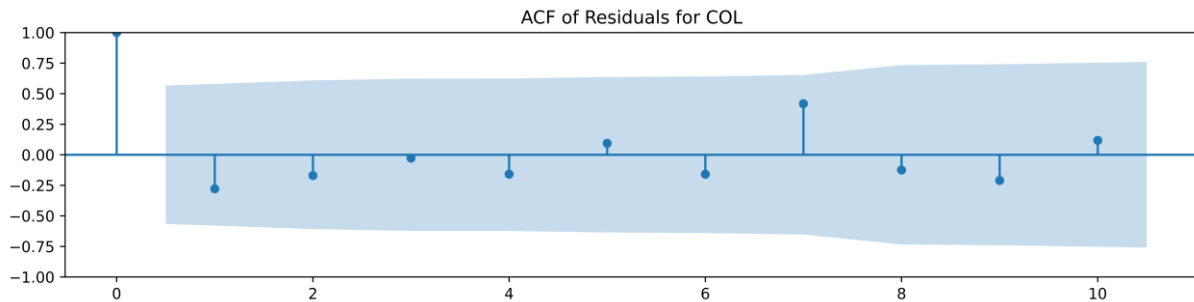


Figure 7. ACF of Lasso Regression Residuals for the COL dataset

The Ljung-Box test (Ljung and Box, 1978) was conducted at lag 4 (statistic = 2.3556, $p = 0.9436$), indicating no significant autocorrelation. This suggests that Lasso effectively captures short-term dependencies within the COL dataset, but certain patterns, particularly non-linear structures, may remain unexplained. The histogram of residuals and the Q-Q plot further provide insights into their distributional properties. The residual histogram (Figure 8, left) exhibits a symmetric, bell-shaped distribution, while the Q-Q plot (Figure 8, right) demonstrates strong alignment with the theoretical quantiles, suggesting that the residuals approximate normality. These findings are statistically supported by the Shapiro-Wilk test ($p = 0.5544$) (Shapiro and Wilk, 1965) and Jarque-Bera test ($p = 0.6868$) (Jarque and Bera, 1987), both of which fail to reject the null hypothesis, indicating that the residuals do not deviate significantly from normality.

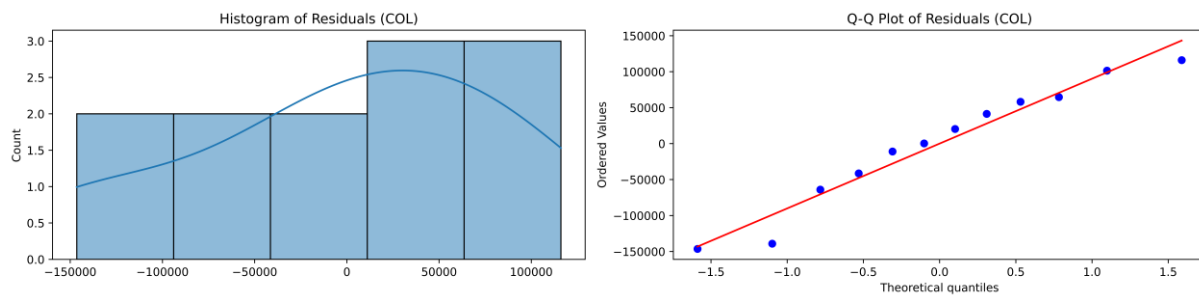


Figure 8. Lasso Regression Residuals Histogram and Q-Q plot

The ADF test confirms that the residuals are stationary (ADF statistic = -4.8288 , $p = 0.0000$), eliminating the need for further transformations such as differencing. However, a crucial observation arises from the BDS test for non-linearity (statistic = -4.6387 , $p = 0.0000$) (Akintunde *et al.*, 2015), which strongly rejects the null hypothesis, indicating the presence of non-linear dependencies in the residuals. This suggests that while Lasso effectively models linear relationships, it fails to fully capture underlying non-linear structures. Given these findings, the incorporation of a Recurrent Neural Network (RNN) is a reasonable next step, as RNNs are well-suited for learning complex temporal dependencies that traditional Regression models cannot capture.

Residual Analysis of Ridge Regression for MKT dataset

Building on the residual diagnostics previously performed for Lasso, the analysis now turns to Ridge Regression to evaluate its adequacy in modelling the MKT dataset. The ACF plot (Figure 9) indicates that most residuals fall within the 95% confidence bands, suggesting that there is no strong autocorrelation at any lag. The Ljung-Box test at lag 4 (statistic = 3.8763 , $p = 0.8436$) confirms this finding, as the high p -value indicates a failure to reject the null hypothesis. This suggests that Ridge Regression adequately captures serial dependencies within the dataset, as there is no evidence of remaining autocorrelation.

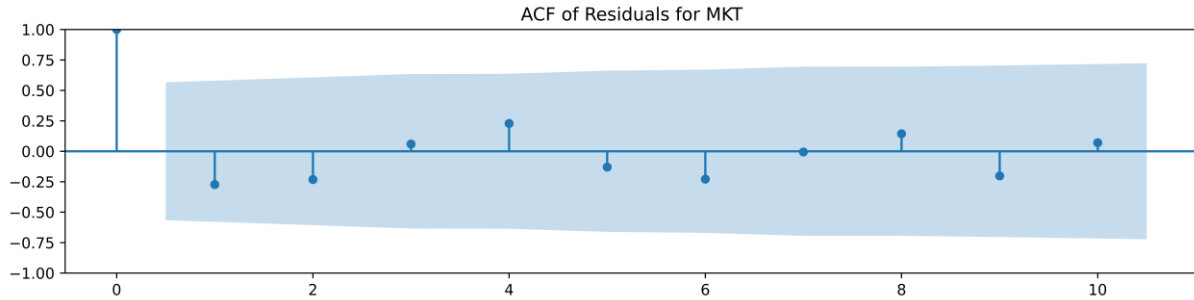


Figure 9. ACF of Ridge Regression Residuals for the MKT dataset

The histogram of residuals (Figure 10, left) exhibits a roughly symmetric shape with a slight peak near the mean, which is generally expected for well-modelled residuals. Additionally, the Q-Q plot (Figure 10, right) demonstrates that most points align closely with the theoretical quantiles, except for minor deviations at the tails. This alignment supports the assumption of approximate normality, though some deviation from perfect normality is expected. Both the Shapiro-Wilk test ($p = 0.0502$) and Jarque-Bera test ($p = 0.0905$) fail to reject the null hypothesis, indicating that the residuals do not significantly deviate from a normal distribution. This result reinforces the visual interpretation of the Q-Q plot.

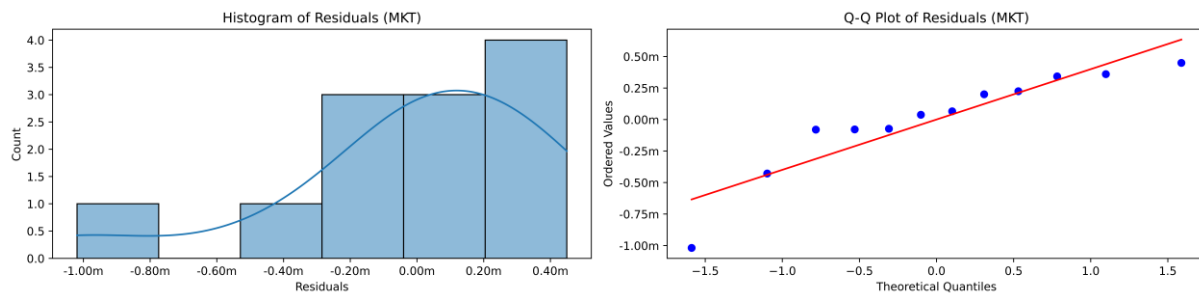


Figure 10. Lasso Regression Residuals Histogram and Q-Q plot

Furthermore, the Augmented Dickey-Fuller (ADF) test (statistic = 13.8945, $p = 1.0000$) indicates the presence of non-stationarity in the residuals. This result suggests that while Ridge Regression effectively captures the linear dependencies within the MKT dataset, it may not fully address underlying trends or persistent patterns that contribute to non-stationarity. However, given that the BDS test (statistic = -0.0559, $p = 0.9555$) fails to reject the null hypothesis of independence, the model does not exhibit significant non-linearity. The detected non-stationarity likely relates to gradual changes or structural shifts rather than complex, non-linear interactions, indicating that linear modelling remains suitable despite some residual non-stationarity.

Therefore, the addition of a Neural Network (NN) such as an RNN is not scientifically justified in this case, as non-linearity is not detected in the residuals. The Ridge Regression model appears sufficient for modelling the linear structure of the MKT dataset, as indicated by the lack of significant autocorrelation and the near-normal distribution of residuals.

Hybrid Lasso-RNN Model for COL dataset

Following the residual analysis of the Lasso Regression model for the COL dataset, a hybrid Lasso-RNN model is proposed to improve forecasting performance. The decision to adopt this approach is based on the detection of statistically significant non-linearity in the Lasso residuals, as indicated by the BDS test. By integrating Lasso Regression to model linear components and a Recurrent Neural Network (RNN) to capture residual non-linear patterns, the hybrid framework aims to enhance forecast accuracy for the period 2022-2030.

The modelling process is structured in two stages. First, Lasso Regression is applied to the historical COL data to extract linear trends, using engineered temporal features such as trend, squared trend, and lagged values. The regularization strength (alpha parameter) is tuned automatically via Optuna to

optimize predictive performance. Once trained, Lasso's residuals, representing unexplained variance, are extracted and standardized to ensure numerical stability.

In the second stage, the residuals are passed to a Recurrent Neural Network designed to model remaining temporal dependencies. A fixed sequence length is used to provide the RNN with adequate temporal context, enabling it to learn patterns across time. The network architecture includes three layers of Simple RNN units with progressively decreasing widths to capture hierarchical patterns, along with batch normalization and dropout to improve generalization. Training is performed using the RMSprop optimizer with weight decay, and early stopping is applied based on validation loss to prevent overfitting. The final forecast is constructed by summing the Lasso prediction and the RNN-generated residual corrections, thereby incorporating both linear and non-linear components.

To assess the hybrid model's effectiveness, its output is compared with actual COL values in the validation period. The model achieves a MAPE of 3.66%, an RMSE of 192,860.87, and an R^2 score of 0.25. The forecasted COL value for 2022 is 4,644,088, resulting in a percentage difference of -6.90%. These results indicate that although non-linearity was detected in the residuals, the added complexity introduced by the RNN did not substantially improve the Lasso Model's performance during the evaluation period.

3.7 Forecasting the European Collection Rate (CR) of WEEE from 2022 to 2030

This section presents the projected trajectory of the European Union's WEEE Collection Rate from 2022 to 2030, derived from the forecasted values of COL and MKT for the EU27. The CR, calculated using the methodology defined in Section 3.4 and aligned with the WEEE Directive's framework, serves as a critical indicator for assessing progress toward European waste management targets.

Based on the comparative analysis in Section 3.7, Lasso Regression was selected as the most effective forecasting model for the COL dataset, while Ridge Regression emerged as the most accurate and generalizable model for the MKT dataset. Their predictions from 2022 to 2030, presented in Table 3, form the basis for calculating the CR over the forecast horizon.

Table 3. Predictions of Lasso and Ridge Regression models for COL and MKT (2022-2030)

Model	2022	2023	2024	2025	2026	2027	2028	2029	2030
Lasso Forecasts (COL)	5,044,847	5,112,456	5,180,065	5,247,674	5,315,284	5,382,893	5,450,502	5,518,111	5,585,721
Ridge Forecasts (MKT)	15,169,037	15,322,297	15,475,557	15,628,817	15,782,077	15,935,337	16,088,597	16,241,857	16,395,117

The forecasted trajectory of the Collection Rate from 2022 to 2030 (Figure 11) reveals a persistent downward trend, starting from 40.5% in 2022 and declining to 34.7% by 2030. These forecasts are evaluated against the WEEE Directive's percentage targets of 45% and 65%, which serve as regulatory benchmarks. The predicted value for 2022 aligns closely with the officially reported EU27 collection rate of 40.1%, as documented by Eurostat (Eurostat, 2024b), thereby reinforcing the validity of the proposed forecasting methodology and the predictive reliability of the Lasso and Ridge Regression models selected for COL and MKT datasets, respectively.

Although the 2022 forecast aligns closely with the observed CR, projections indicate a persistent failure to meet the WEEE Directive's 45% and 65% targets throughout the forecast horizon. This downward trajectory is primarily driven by a disproportionate increase in the denominator, namely EEE placed on the market, relative to the growth in WEEE collection volumes. Given the definition of the Collection Rate as established in Directive 2012/19/EU, this structural imbalance inevitably results in lower CR values over time, unless significant policy or behavioural changes are introduced to enhance collection volumes.

This observation highlights the systemic limitations of existing WEEE collection mechanisms across the EU. As emphasized in studies by Cucchiella et al. (2015) and Milios (2018), the effectiveness of collection systems is constrained by a multitude of factors, including insufficient infrastructure, fragmented stakeholder coordination, inadequate consumer incentives, and limited public engagement in recycling practices. Furthermore, research by Kumar et al. (2017) underscores that consumer awareness and accessibility to collection channels are critical determinants of WEEE return behaviour.

Consequently, achieving the 65% target will likely require a comprehensive policy mix, incorporating enhanced extended producer responsibility (EPR) schemes, financial incentives for consumers, improved traceability and monitoring systems, and investment in logistics and digital technologies to optimize reverse supply chains (Forti *et al.*, 2020).

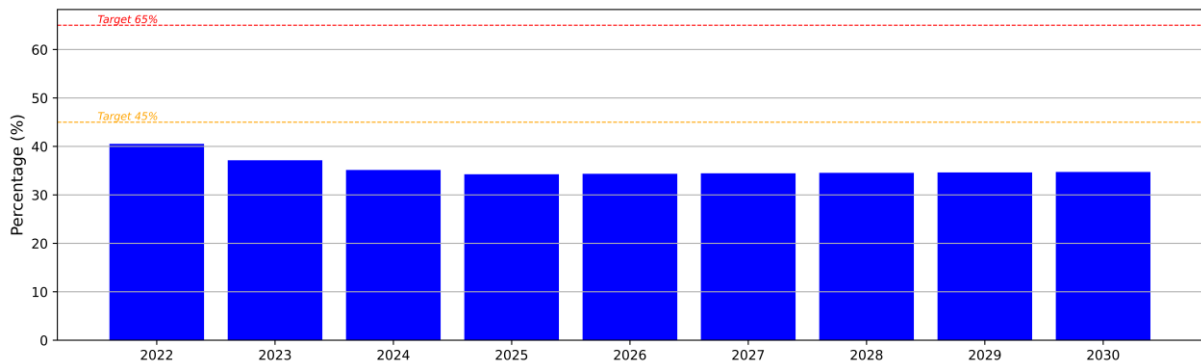


Figure 11. Forecasted European WEEE Collection Rate (2022-2030) using Lasso and Ridge Regression models

Additionally, it is important to recognize that a decline in the Collection Rate (CR), even when the amount of waste collected remains stable or increases, does not necessarily reflect a failure in collection efforts. Instead, it may result from a disproportionate rise in market input (EEE), driven by factors such as technological advancement, increased consumer demand, and market expansion. Therefore, future policy frameworks should aim not only to increase WEEE returns, but also to address upstream drivers such as consumption patterns and product design, in order to reduce overall e-waste generation. These priorities align with the objectives of the EU Circular Economy Action Plan (European Commission, 2020b, 2020a) and Sustainable Development Goals.

3.8 Strengths and Limitations of the Study

This study presents a methodologically strong and multidimensional predictive framework to evaluate the European Union's capacity to meet WEEE collection targets in alignment with the 2030 Agenda for Sustainable Development. The analysis is conducted at the EU27 aggregate level using annual observations for COL and MKT, and the forecasting task is formulated primarily as a univariate problem. Consequently, projections are anchored in the historical dynamics of the observed series and do not explicitly incorporate exogenous drivers or structural policy variables.

A key strength lies in the comprehensive integration of Statistical, ML, DL, and Hybrid modelling techniques. The systematic evaluation of baseline, classical, and advanced models, including the Lasso RNN hybrid, enabled the selection of the most appropriate forecasting strategy for each dataset (COL and MKT), thereby enhancing the study's analytical precision and methodological transparency. Another major contribution is the study's commitment to empirical validation. Model outputs were benchmarked against the actual 2022 values, demonstrating close alignment with Eurostat-reported figures. In addition, comprehensive residual diagnostics, including tests for normality, stationarity, and non-linearity, strengthened the validity of the model selection process and the rationale for hybridization, reducing the risk of overfitting and improving generalizability.

The forecasting of the Collection Rate (CR) strictly followed the methodology prescribed in the WEEE Directive, reinforcing the study's policy relevance and practical applicability. By incorporating the predicted values of COL and MKT into the official CR formula, the research provides actionable insights for regulatory monitoring. Furthermore, missing data were addressed using scientifically validated imputation techniques, supported by cross-validation against external socioeconomic indicators, which strengthens the internal validity of the derived datasets.

Nevertheless, several limitations must be acknowledged. First, the time series used for modelling includes only 17 annual observations, which constrains statistical power and the complexity that can be supported reliably, particularly for DL models that typically require larger datasets. Although

regularization strategies, dropout layers, and early stopping were employed to mitigate overfitting, the limited sample inherently restricts the models' ability to learn more intricate temporal dynamics, especially for MKT. Second, the models do not explicitly account for structural breaks or external shocks that may substantially alter future market trends or waste generation patterns. As a result, abrupt or non-recurring shifts may be underrepresented in the forecasts. Moreover, the EU27 aggregate perspective can mask substantial heterogeneity across Member States, which differs in collection infrastructure, enforcement intensity, and consumer return behavior. Therefore, the forecasts should be interpreted as a Union-wide trajectory rather than as a proxy for country-specific performance. Third, hybrid models are inherently data-dependent. In this study, the hybrid Lasso-RNN model did not surpass the standalone Lasso model for COL. The RNN component improved the modelling of residual non-linearities, yet the added complexity did not translate into measurable performance gains. This outcome underscores that hybridization should be adopted on empirical grounds rather than theoretical appeal. Lastly, although the CR forecasts adhere to the WEEE Directive methodology, the framework remains limited in explanatory scope because it does not incorporate behavioral and structural drivers. Future research could integrate such indicators to enhance explanatory power and support more targeted policy interventions.

4. Conclusions

This study developed an integrated predictive framework to forecast the WEEE Collection Rate (CR) across the European Union (EU27) from 2022 to 2030. The framework incorporated a wide range of predictive modelling techniques, including statistical time series models, ML algorithms, DL architectures, and a Hybrid model designed to capture both linear and non-linear dependencies. The modelling process was supported by systematic preprocessing procedures, including the imputation of missing values using linear interpolation validated through macroeconomic and environmental indicators.

The results highlight the superiority of Lasso and Ridge Regression in forecasting the COL and MKT datasets, respectively. Residual analysis revealed non-linear structures in the Lasso model, which justified the development of a hybrid Lasso-RNN model. Nonetheless, the hybrid did not yield significant performance gains over the standalone Lasso, indicating that the latter already captured most of the predictive structure in the COL dataset. DL models, particularly Recurrent Neural Networks (RNNs), also demonstrated strong performance in modelling complex temporal dynamics, especially for the MKT dataset.

Despite the methodological rigor, the forecasted CR remains below the 65% target mandated by the WEEE Directive throughout the 2022-2030 horizon. This persistent gap stems primarily from the rising volume of EEE placed on the market, which is not met with a commensurate increase in WEEE collection. The resulting decline in CR underscores the limitations of current policy mechanisms and signals the need for enhanced regulatory strategies, infrastructure investments, and public engagement to support target compliance.

The proposed framework constitutes a replicable and empirically validated tool to support forward-looking planning and regulatory monitoring. By aligning with the objectives of the Sustainable Development Goals, particularly those concerning sustainable production and resource efficiency, it contributes actionable insights toward advancing the circular transition of Europe's waste management system. Future work may explore scenario-based extensions, country-specific disaggregation, and the integration of behavioural and infrastructural variables to enhance the explanatory power of the forecasts.

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