

Circular Economy-Oriented Routing of End-of-Life Smartphones: A Device Circularity Readiness Score and Bi-Objective NSGA-II Optimization Framework

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Abstract

The rapid growth of electronic waste, particularly from smartphones, highlights the need for more effective circular economy strategies. Although extending device lifespans can significantly reduce environmental impact, selecting the most suitable end-of-life option, such as reuse, repair, or recycling, remains a complex decision problem. This complexity arises from differences in device conditions and the need to consider multiple criteria simultaneously. This study proposes a structured framework to address this challenge by combining technical evaluation with multi-objective optimisation. First, a Device Circularity Readiness Score is developed to assess each smartphone based on battery condition, technical performance, and repairability. Then, a bi-objective optimisation model based on the NSGA-II algorithm is applied to determine optimal routing decisions by balancing economic value recovery and CO₂ emissions reduction. In addition, the readiness score is integrated as a constraint to ensure that all decisions remain technically feasible. The proposed framework provides a practical and data-driven approach for improving circular decision-making in smartphone waste management and contributes to more efficient and sustainable resource use.

Keywords

Circular Economy, Multi-Objective Optimization, End-of-life Strategies, Sustainability, E-Waste

1. Introduction

The generation of electronic waste (e-waste) has reached unprecedented levels, with 62 million metric tons produced globally in 2022 and projections reaching 82 million metric tons by 2030. However, only 22,3% is formally collected and recycled, creating significant environmental and public health risks. Smartphones are a major contributor due to their widespread use and short replacement cycles. With over 7 billion users worldwide and annual shipments of approximately 1,24 billion units (IDC, 2025), devices are replaced on average every 21,6 months, often while still functional (Cordella et al., 2021).

Since a single smartphone generates about 85,2 kg CO₂-equivalent emissions and production accounts for nearly 83% of lifecycle emissions, extending product lifetime is one of the most effective strategies for reducing environmental impact (ADEME, 2022; Deloitte, 2022). The circular economy offers an alternative to the linear “take–make–dispose” model by promoting reuse, repair, refurbishment, and recycling (Potting et al., 2017). For smartphones, the main

pathways are resale, repair, and recycling. Their economic relevance is increasing, with the refurbished smartphone market valued at USD 62,48 billion in 2024 and projected to reach USD 117,28 billion by 2034 (Expert Market Research, 2025). Used and refurbished smartphone sales also grew in 2022–2023, while new smartphone sales declined (GSMA, 2025).

Despite this growth, selecting the optimal circular pathway remains complex due to trade-offs involving device condition, battery health, repairability, technical performance, and market value. Existing studies either focus on environmental impacts or reverse logistics efficiency, without integrating device-level technical assessment and multi-objective optimization. This study addresses this gap using a dataset of 3.454 used smartphones from Kaggle (Ahsan, 2021). The results reveal a strong trade-off between economic and environmental objectives, suggesting that the second-hand smartphone ecosystem already operates close to its circular efficiency frontier.

2. Literature Review

2.1. Circular Economy

The world's population has been growing steadily since 2019 at a rate of 0.88% per year (Worldometer, 2024), contributing to a 1.1% increase in CO₂ emissions (Statista, 2023) alongside accelerating urbanization, resource depletion, and waste generation. Global waste production is projected to rise by more than 50% and reach 3.8 billion tons annually by 2050 (Geissdoerfer et al., 2017), while material consumption has already exceeded 100 billion tons per year and is expected to increase by another 50% by mid-century (Circularity Gap Report, 2025).

In response, the circular economy has gained importance in both academic and policy contexts as an alternative to linear production systems. It is generally defined as an economic model that promotes the circular flow of resources through reuse, recycling, and efficient utilization to minimize waste (EIB, 2020). The European Investment Bank emphasizes durable, repairable, and recyclable products as key elements of more sustainable production and consumption systems (EIB, 2024), while the OECD defines it as a model aimed at maintaining product and material value in the economy for as long as possible while reducing waste generation (OECD, 2024).

The linear “take–make–dispose” model relies on a one-way flow of resources from extraction to disposal, with cities acting as consumption and waste hubs and rural areas supplying raw materials. In contrast, the circular economy treats materials as long-term assets, aiming to preserve their value through reuse, repair, and recycling while separating biological and technical cycles (Domenech & Borrión, 2022).

2.2. Environmental Evidence from Life Cycle Assessment Studies

Life cycle assessment (LCA) is the main method used to evaluate the environmental impacts of circular strategies for smartphones. It allows a full analysis of impacts across all lifecycle stages, from raw material extraction to end-of-life and provides a consistent basis for comparison (Segura-Salazar et al., 2019; Cordella et al., 2021). A baseline carbon footprint for a new smartphone is important to measure the benefits of circular options.

LCA studies show that most environmental impact comes from the production phase. Cordella et al. (2021) find that material extraction, processing, and manufacturing dominate emissions, with key components responsible for about 75% of material-related impacts. Over a 4.5-year lifespan, total emissions reach around 77.2 kg CO₂eq. Similarly, Deloitte (2022) reports that 83% of global smartphone emissions come from manufacturing, logistics, and initial use. This explains why extending product lifetime is very effective.

The literature shows a clear hierarchy of circular strategies. Reuse and lifetime extension provide the highest benefits, reducing emissions by 52–79% and up to 30–50%, respectively (Cordella et al., 2021). Refurbishment is also highly effective, with up to 91% lower emissions compared to new devices (ADEME, 2022). Scenario studies confirm that refurbishment performs better than repair and remanufacturing due to longer usage (Pamminger et al., 2021). However, repair outcomes depend on product reliability. Market conditions also affect results. The benefits of reuse depend on whether second-hand devices replace new ones; otherwise, gains may decrease. In comparison, recycling has limited impact, reducing emissions by about 5%, and depends on material displacement (Cordella et al., 2021). Therefore, it is considered a last option.

2.3. Multi-Objective Optimization in Circular Supply Chains

In circular economy routing problems, decision-makers must optimise conflicting objectives simultaneously, as improvements in economic value recovery may reduce environmental performance. Multi-objective optimisation addresses these trade-offs by generating a Pareto frontier of non-dominated solutions, where no objective can be improved without worsening another (Deb et al., 2002; Blank & Deb, 2020). Several solution approaches exist. Exact methods become computationally expensive for large problems (Labbi & Ahmadi, 2024), while weighted-sum methods may fail to capture non-convex Pareto solutions (Wang et al., 2022). Metaheuristic approaches overcome these limitations by generating multiple Pareto-optimal solutions in a single run (Deb et al., 2002).

Among them, NSGA-II is widely used in supply chain optimisation (Tirkolaee et al., 2022). Through non-dominated sorting and crowding distance mechanisms, it balances convergence and solution diversity (Deb et al., 2002; Blank & Deb, 2020). Compared with multi-objective particle swarm optimisation, NSGA-II generally provides more stable solution quality, although with higher computational effort (Babaeinesami et al., 2022). Consistent with previous circular and closed-loop supply chain studies, NSGA-II is adopted in this research (Babaeinesami et al., 2022; Tirkolaee et al., 2022).

2.4. Ranking Alternatives with MCDM Method

TOPSIS is a multi-criteria decision method that ranks alternatives based on distance from ideal best and worst solutions (Hwang & Yoon, 2012). In circular economy studies, it is commonly used as a post-processing step to select a single solution from Pareto-optimal sets (Chen et al., 2024). Mardani et al. (2015) identify TOPSIS as one of the most widely used ranking methods due to its ability to manage multiple conflicting criteria. In e-waste applications, Chen et al. (2024) combined TOPSIS with NSGA-II and MOPSO to select balanced solutions in smartphone reverse logistics.

3. Proposed Methodology

This section presents a framework for routing end-of-life smartphones into optimal circular economy pathways. It integrates a Device Circularity Readiness Score (DCRS), based on battery state, technical sufficiency, and reparability, with a cluster-based NSGA-II optimization to balance economic and environmental objectives. K-means clustering is used for dimensionality reduction, enabling efficient large-scale decision-making in a closed-loop supply chain. The flowchart is shown in Figure 1.

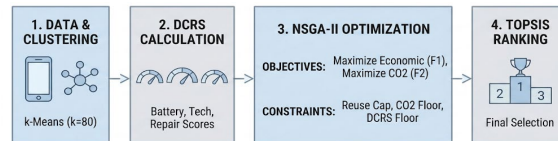


Figure 1. Flowchart of the proposed methodology

3.1 Dataset

The empirical foundation of this research is the "Used Phones & Tablets Pricing Dataset" an extensive secondary data source retrieved from the Kaggle repository (Ahsan, 2021). The dataset consists of 3,454 individual device records, providing a granular look at the secondary mobile market. The temporal scope of the data covers devices released between 2013 and 2020, representing a diverse range of technological generations and hardware architectures. Furthermore, the dataset's composition is highly representative of global usage patterns; Android-based devices account for 93.1% of the total observations, aligning with the market distribution reports provided by IDC (2025).

3.2 Device Circularity Readiness Score (DCRS) Construction

The DCRS measures how technically ready a device is for each circular pathway. It is built from three sub-scores, each based on a specific set of literature. The scores are then combined with different weights for each pathway to produce three DCRS values per device — one for Reuse, one for Repair, and one for Recycle. An important design requirement is that the DCRS must not use price or CO₂ data.

3.2.1 Battery State Score (BSS)

The BSS measures the battery condition of a device. It has two parts: how much the battery has degraded over time, and how large the original battery capacity is compared to the market average. According to IEC 61960-3:2017, lithium-ion batteries lose about 20% of their capacity after 500 full charge cycles. If we assume one charge per day, this gives a daily degradation rate of 0.0004. The second part compares the device's battery capacity to the dataset median. This follows the functional adequacy approach of Islam and Huda. (2018). Both parts are clipped between 0 and 1. The equal weighting comes from Cordella et al. (2021), who found that battery failure causes 42% of all smartphone replacements. This makes both degradation and original capacity equally important. The formula is:

$$BSS = 0.5 \times (1 - 0.0004 \times \text{days_used}) + 0.5 \times (\text{battery} / \text{median_battery})$$

3.2.2 Technical Sufficiency Score (TSS)

The TSS measures a device's technical suitability for second life using RAM, internal memory, and connectivity. RAM carries the highest weight (0,45) as the strongest predictor of remaining usability; Islam and Huda (2018) show that insufficient RAM prevents modern OS and app performance. Scores are benchmarked to the dataset median (4 GB), normalized, and capped at 1,0. Connectivity is weighted at 0,35, reflecting its effect on usability; GSMA (2023) reports that 5G devices remain in use about 18 months longer than 4G devices, so 5G is scored 1,00 and 4G as 0,60. Internal memory has the lowest weight (0,20), as Wilson et al. (2017) find its impact is partially mitigated by cloud storage, making it less critical than RAM and connectivity.

$$TSS = 0.45 \times (\text{RAM} / \text{median_RAM}) + 0.35 \times \text{connectivity} + 0.20 \times (\text{memory} / \text{median_memory})$$

3.2.3 Repairability Score (RS)

The RS evaluates how easily a device can be repaired, based on spare-parts availability and physical repairability. Spare-parts availability has the highest weight (0.65), as it is the main constraint on repair feasibility (Ahmed et al., 2025). The seven-year supply requirement defined by EU Regulation 2024/1781 is used as the reference. Physical repairability is weighted at 0.35. Barros and Dimla (2023) show that design factors, especially disassembly complexity, are key determinants of repairability. The 65%/35% weighting is based on Ahmed et al. (2025), who showed that spare-parts access is the main barrier to repair, while physical design features play a secondary but meaningful role.

$$\begin{aligned} AS &= \max(0, 1 - (\text{evaluation_year} - \text{release_year}) / 7) \\ RS_physical &= \max(0, 1 - 0.5 \times (\text{weight} / \text{max_weight}) - 0.5 \times (\text{screen_size} / \text{max_screen})) \\ RS &= 0.65 \times AS + 0.35 \times RS_physical \end{aligned}$$

3.2.4 Remaining Functional Life (RFL)

The RFL shows what proportion of a device's maximum technical lifespan has not yet been used. Without direct battery health measurements, we cannot measure this precisely. However, EU Regulation 2024/1781 defines a seven-year regulatory lifespan as the baseline for spare-parts obligations. This study uses this regulatory period as the reference. A device with RFL = 0 has already exceeded the seven-year limit. A device with RFL close to 1 has barely been used. The formula is:

$$RFL = \max(0, 1 - \text{days_used} / (7 \times 365))$$

3.2.5 Pathway-Specific DCRS

Once the sub-scores are calculated, they are combined into pathway-specific DCRS values. The weights are different for each pathway because each pathway has different technical requirements. Pamminger et al. (2021) and Ahmed et al. (2025) provide the basis for these choices. The formulas are:

$$\begin{aligned} DCRS_{reuse} &= 0.45 \times BSS + 0.40 \times TSS + 0.15 \times RS \\ DCRS_{repair} &= 0.25 \times BSS + 0.20 \times TSS + 0.55 \times RS \\ DCRS_{recycle} &= 0.40 \times (1 - BSS) + 0.30 \times (1 - TSS) + 0.30 \times (1 - RS) \end{aligned}$$

For reuse, BSS receives the highest weight (0,45) because battery condition is the primary determinant of second-hand acceptance (Cordella et al., 2021), followed by TSS (0,40) reflecting performance and connectivity (Makov et al., 2019), while RS has a smaller role (0,15). For repair, RS is dominant (0,55) since design and spare-parts availability determine feasibility (Barros and Dimla, 2023; EU Regulation 2024/1781), with BSS weighted at 0,25

and TSS at 0,20. For recycling, lower-quality devices are prioritised by inverting the scores: (1–BSS) carries the highest weight (0,40), while (1–TSS) and (1–RS) are equally weighted at 0,30.

3.3 Bi-Objective NSGA-II Optimization Model

The circular routing problem is formulated as a bi-objective optimization with 80 decision variables (one per cluster), each assigned to reuse (0), repair (1), or recycle (2). Two objectives are maximized. F1 maximizes economic value recovery across all devices:

$$\text{Maximise } F1 = \frac{1}{N} \sum_c \alpha_j(c) \text{ VRS}_c n_c$$

where α_j is the pathway-specific value retention coefficient, VRS_c is the cluster mean value retention ratio, and n_c is the number of devices in cluster c . Coefficients reflect value capture: reuse = 1.00 (full value transfer), repair = 0.77 (second-life value share), and recycle = 0.05 (material recovery only) (Makov et al., 2019; Pamminger et al., 2021; Cordella et al., 2021). F2 maximises total CO₂ avoidance:

$$\text{Maximise } F2 = \frac{1}{N} \sum_c \text{CO}_{2j}(c) \text{ RFL}_c n_c$$

where CO_{2j} is the baseline CO₂ avoidance coefficient for pathway j , and RFL_c is the cluster mean remaining functional life. The CO₂ coefficients were derived from the LCA study of Cordella et al. (2021), which estimates a baseline footprint of 77.2 kg CO₂-eq per smartphone. Conservative values of 40.1 kg CO₂-eq for reuse (52% reduction), 17.8 kg CO₂-eq for repair (23% reduction), and 3.9 kg CO₂-eq for recycling (5% reduction) were adopted. Rather than conducting an independent life-cycle assessment, this study adopts secondary emission factors from the peer-reviewed LCA of Cordella et al. (2021); the pathway-specific coefficients are derived by applying the reported reduction rates (52%, 23%, and 5% for reuse, repair, and recycling, respectively) to the baseline footprint of 77.2 kg CO₂-eq. The RFL multiplier adjusts CO₂ savings according to remaining functional life, as shorter second-life use yields lower environmental benefits (Makov et al., 2019). To ensure realistic and feasible outcomes, three inequality constraints imposing minimum standards were incorporated into the optimization model, as summarized in Table 1.

Table 1. Optimization Constraints

Constraint	Condition	Rationale
G1 — Reuse cap	Reuse ratio $\leq 60\%$	Expert Market Research (2025): market absorption limit
G2 — CO ₂ floor	CO ₂ savings $\geq 30\%$ of max achievable	Cordella et al. (2021); EU Green Deal ICT targets
G3 — Circularity floor	DCRS ≥ 0.65	Chen et al. (2024): structural alignment mitigation via constraint
Eligibility — Reuse	BSS ≥ 0.60 ; TSS ≥ 0.40 ; RFL ≥ 0.20	Cordella et al. (2021); Makov et al. (2019)
Eligibility — Repair	RS ≥ 0.15 ; RFL ≥ 0.08	Barros and Dimla (2023); EU Reg. 2024/1781

Three system-level constraints define the feasible solution space. G1 limits reuse to 60% to reflect market capacity, as higher allocations could exceed demand despite the growth of the second-hand market (Expert Market Research, 2025). G2 requires total CO₂ savings to reach at least 30% of the maximum, consistent with the lower bound reported for repair scenarios (Cordella et al., 2021).

At the device level, eligibility conditions determine pathway access. Reuse (E1) requires BSS ≥ 0.60 , TSS ≥ 0.40 , and RFL ≥ 0.20 , ensuring acceptable battery condition, technical performance, and approximately 17 months of remaining life (Cordella et al., 2021; Islam and Huda, 2018). Repair (E2) requires RS ≥ 0.15 and RFL ≥ 0.08 , reflecting minimum repairability standards and economic feasibility (EU Regulation 2024/1781; Pamminger et al., 2021). Recycling (E3) has no eligibility constraints and serves as the default option when other conditions are not met.

3.4 TOPSIS

NSGA-II generates 100 Pareto-optimal solutions. TOPSIS (Hwang & Yoon, 2012) is used to select one final solution by ranking alternatives based on their Euclidean distance to the ideal best (max F1, F2) and ideal worst (min F1, F2). The preferred solution maximizes the closeness coefficient. Three weighting scenarios are applied. The economy-priority case uses $w_{F1} = 0.7$, $w_{F2} = 0.3$, reflecting a revenue-focused decision-maker. The environment-priority case uses $w_{F1} = 0.3$, $w_{F2} = 0.7$, reflecting a CO₂-focused perspective. The balanced case assigns equal weights ($w_{F1} = w_{F2} = 0.5$), following Chen et al. (2024), and serves as the baseline scenario.

4. Application

4.1 Dataset and Descriptive Statistics

Each record in the dataset is defined by 16 variables that encompass the physical, technical, and economic attributes of the handheld devices. Table 2 provides an exhaustive breakdown of the dataset's features and their data types

Table 2. Exhaustive Description of Dataset Features and Their Functional Roles

Type	Feature Name	
Numerical	Screen Size	Days Used
	Weight	Battery Capacity
	Normalized New Price	RAM
	Normalized Used Price	Internal Memory
	Camera Resolution	
Categorical	Brand	Connectivity
Temporal	Release Year	

Before applying NSGA-II, an exploratory analysis of the cleaned dataset was conducted to understand the smartphone population. This step identifies the key technical, temporal, and economic characteristics used in the model. Table 3 presents descriptive statistics of the main variables used for the DCRS and the objective functions.

Table 3. Descriptive Statistics of Key Variables (Raw Dataset, n = 3,454)

Variable	Count	Mean	Std. Dev.	Min	25th %	Median	Max
battery (mAh)	3,448	3,133	1,300	500	2,100	3,000	9,720
ram (GB)	3,450	4.04	1.37	0.02	4.00	4.00	12.00
internal memory (GB)	3,450	54.57	84.97	0.01	16.00	32.00	1,024
weight (g)	3,447	182.75	88.41	69	142	160	855
screen_size (cm)	3,454	13.71	3.81	5.08	12.70	12.83	30.71
days_used	3,454	674.87	248.58	91	533.5	690.5	1,094
release_year	3,454	2016.0	2.30	2013	2014	2016	2020
VRS	3,454	0.840	0.071	0.430	0.800	0.840	1.000

The dataset shows strong heterogeneity in technical specifications, reflecting the diverse structure of the secondary smartphone market. Battery capacity ranges from 500 to 9,720 mAh, with an average of 3,133 mAh. RAM and storage also vary widely; median RAM is 4 GB, while storage reaches up to 1,024 GB. Temporal variables highlight relatively short usage periods. The average days_used is 674.87 days (range: 91–1,094), which is well below the 7-year (2,555-day) regulatory lifespan defined by EU Regulation 2024/1781. This supports evidence that smartphones are replaced long before their technical end-of-life. Economically, the Value Retention Score (VRS) averages 0.84 with low variation (SD 0.071), indicating relatively uniform pricing in the secondary market. Overall, these patterns support the definition of eligibility rules and the interpretation of Pareto solutions.

Figure 2 further illustrates the dataset structure. It shows a strong concentration of devices from major brands, mainly released between 2014 and 2018. It also confirms short usage periods (mean 674.87 days) and a narrow VRS distribution around the median of 0.84, reinforcing the observed technical and economic consistency in the dataset.

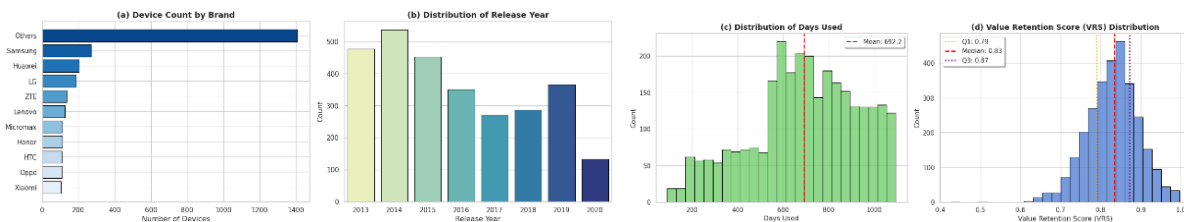


Figure 2. Dataset composition and key variable distributions (n = 3,454 before cleaning).

The dataset is checked for missing values before sub-score calculation. A complete-case approach is used, removing observations with missing values in variables required for DCRS and objective functions. Since missingness is low (maximum 5.18% for rear_camera_mp, not used in scoring), the final dataset includes 3,165 observations (91.6% of the original). No imputation is applied to avoid bias in optimization inputs. For weight and screen_size, which are used in RS normalization, outliers are treated using the $1.5 \times \text{IQR}$ rule. This prevents extreme values from distorting normalization ratios (e.g., weight-based scaling).

4.2 Device Circularity Readiness Score (DCRS) Calculation

Table 4 presents descriptive statistics for all four sub-scores and VRS across the cleaned dataset.

Table 4. Descriptive Statistics of DCRS Sub-Scores and VRS (n = 3,165)

Sub-Score	Mean	Std. Dev.	Min	Median	Max
BSS	0.793	0.113	0.427	0.815	0.982
TSS	0.796	0.117	0.213	0.860	1.000
RS	0.392	0.180	0.029	0.356	0.892
RFL	0.292	0.213	0.000	0.282	0.899
VRS	0.840	0.071	0.430	0.840	1.000

The mean BSS (0.793) indicates that devices retain about 79% of their battery capacity, consistent with an average usage of ~690 days. Similarly, the mean TSS (0.796) shows that most devices remain close to median market specifications. In contrast, the mean RS (0.392) is lower, mainly due to device age. Since many models were released between 2013 and 2016 and evaluated in 2021, their spare-parts availability declines, often reaching zero, which compresses the RS distribution. This has direct implications for eligibility in the repair pathway. The mean RFL (0.292) suggests that devices have used about 70.8% of their regulatory lifespan, leaving limited remaining life. Figure 3 confirms these patterns: BSS and TSS are generally high, while RS and RFL are low. This explains why many devices do not meet reuse or repair criteria and are instead directed to recycling.

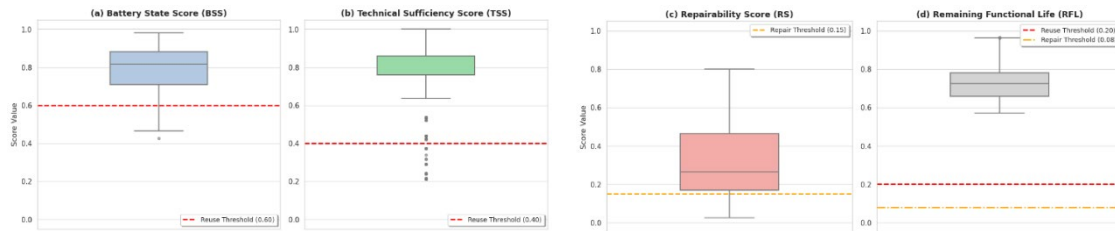


Figure 3. Distribution of DCRS sub-scores

After computing the four sub-scores, pathway-specific DCRS values are calculated using different weights. For reuse, BSS (0.45) and TSS (0.40) are prioritised, as good technical condition is required. For repair, RS has the highest weight (0.55), reflecting the importance of repairability. For recycling, inverted scores ($1 - \text{BSS}$), ($1 - \text{TSS}$), ($1 - \text{RS}$) are used so that lower-quality devices receive higher recycle-readiness scores.

4.4 Dimensionality Reduction: K-Means Clustering

Applying NSGA-II directly to 3,165 devices would be computationally infeasible due to the large number of decision variables. Therefore, K-Means clustering is used to group devices into 80 representative clusters based on BSS, TSS, RS, RFL, and VRS (Table 8). The optimal number of clusters ($k = 80$) is determined using the Elbow Method, where the WCSS curve shows diminishing improvements beyond this point. All features are already scaled within $[0,1]$, so no additional normalization is required. Each cluster is represented by the mean values of the five features, and the number of devices in each cluster is used as a weight in the NSGA-II objective functions. This approach significantly reduces dimensionality while preserving the distributional structure of the dataset. Figure 4 confirms the selection of $k = 80$, as variance reduction becomes marginal beyond this level.

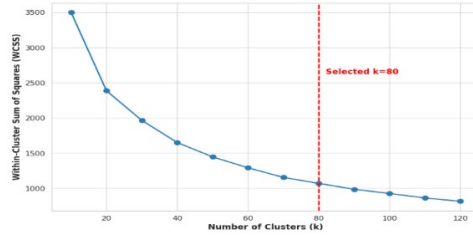


Figure 4. Elbow Method for K-Means cluster number selection

4.5 NSGA-II Multi-Objective Optimisation

After clustering, the problem includes 80 integer decision variables (0 = Reuse, 1 = Repair, 2 = Recycle). The model maximizes F1 (economic value) and F2 (CO₂ avoidance) under system-level and device-level constraints. Table 5 summarizes the algorithm configuration. A population size of 100 and 300 generations are used to ensure convergence. SBX crossover (prob = 0.9, $\eta = 15$) balances exploration and exploitation, while polynomial mutation (prob = $1/n_var \approx 0.0125$, $\eta = 20$) introduces controlled variability without premature convergence.

Table 5. NSGA-II Algorithm Configuration

Parameter	Value
Population size	100
Number of generations	300
Crossover operator	SBX, prob = 0.9, $\eta = 15$
Mutation operator	PM, prob = $1/n_var$, $\eta = 20$

4.5.2 Convergence Analysis

Convergence is evaluated using the Hypervolume (HV) indicator, measured against a reference point set at 110% of the maximum objective values. HV increases rapidly in early generations and stabilises around generation 230, indicating convergence. Figure 5 confirms this pattern, showing a steep initial increase followed by a clear plateau. This supports the use of 300 generations as a sufficient stopping criterion without unnecessary computational cost.

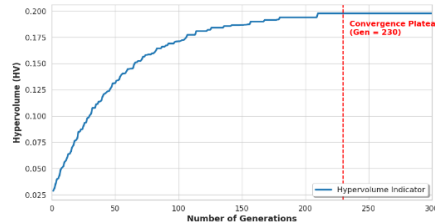


Figure 5. NSGA-II convergence

5. Results and Discussion

After 300 generations, the NSGA-II algorithm identifies 100 non-dominated solutions constituting the Pareto frontier. Table 6 presents the summary statistics for all three output variables across these solutions.

Table 6. Statistical Summary of Pareto Front Solutions

Metric	Min	Mean	Max	Std. Dev.	Unit
F1 — Economic Recovery Ratio	0.7542	0.7545	0.7548	0.0002	ratio
F2 — CO ₂ Avoidance	24.46	24.52	24.56	0.030	kg CO ₂ eq
F1 vs F2 Pearson correlation	$r = -0.956$ ($p < 0.001$)				—
Hypervolume Indicator (HV)	HV = 0.1945 (7.5× improvement over tri-objective formulation HV = 0.025)				—

The Pearson correlation between F1 and F2 is strongly negative ($r = -0.956$, $p < 0.001$), confirming a clear trade-off between economic value and CO₂ avoidance. This trade-off reflects pathway dynamics. Shifting from Repair to Reuse increases F1 ($\alpha = 1.00$ vs. 0.77) but may reduce F2 for devices with low RFL, as CO₂ savings under Reuse depend on remaining lifespan. In contrast, Repair improves F2 for high-RFL devices but yields lower economic returns. Figure 6 illustrates the Pareto frontier, showing the 100 solutions across F1–F2 space and highlighting three TOPSIS-based scenarios (economic, environmental, balanced), which clearly demonstrate the trade-offs between objectives.

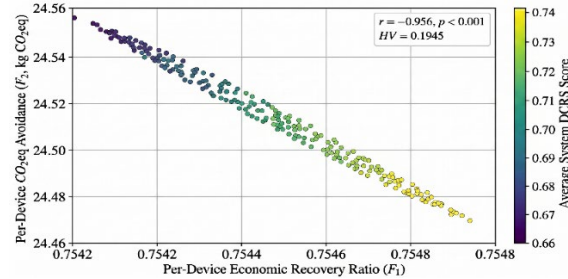


Figure 6. Pareto frontier of the bi-objective optimisation

The Pareto frontier is narrow due to dataset structure rather than the optimization method. About 34% of devices are directly assigned to recycling because they do not meet reuse or repair requirements, which reduces the solution space. Similar market values and lifespans further limit variability, indicating the system operates near its structural efficiency limit. To derive a single routing decision, TOPSIS (Hwang & Yoon, 2012) is applied under three scenarios. The closeness coefficient is computed for 100 Pareto solutions, and the highest value is selected for each scenario. Results are shown in Table 7.

Table 7. TOPSIS Solution Selection Results by Stakeholder Scenario

Scenario (w_{F1} / w_{F2})	F1 Selected (Ratio)	F2 Selected (kg CO ₂)	% Reuse	% Repair
Economy-priority (0.7 / 0.3)	0.7557	25.43	56.6%	16.7%
Environment-priority (0.3 / 0.7)	0.6878	29.53	40.6%	24.7%
Balanced (0.5 / 0.5)	0.7037	28.76	41.2%	24.4%

Figure 7 supports these findings by showing device allocation across pathways for each scenario. The economy-priority case favours Reuse to maximize profit, while the environment-priority case increases Repair to improve CO₂ savings. The balanced scenario combines both, providing a compromise between economic and environmental objectives.

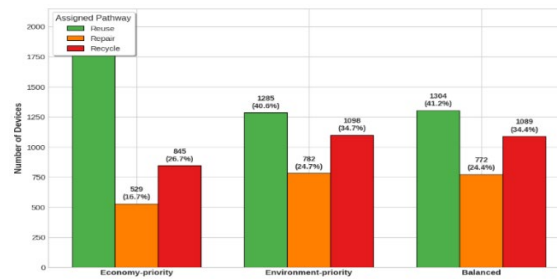


Figure 7. Pathway device distribution for each TOPSIS scenario

Figure 8 shows the routing of 3,165 devices in the BSS–RS space for the balanced TOPSIS solution. It indicates that RS is the main factor separating pathways: devices with $RS < 0.15$ are assigned to Recycle, while those with $RS \geq 0.15$ and $BSS \geq 0.60$ are mainly assigned to Reuse.

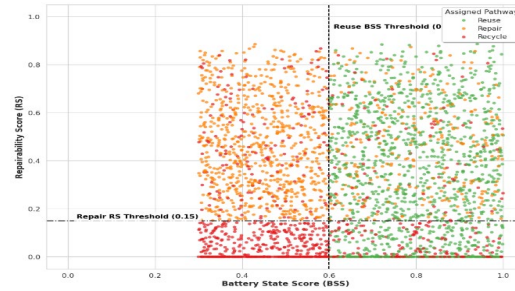


Figure 8. Device-level pathway assignments in the BSS–RS feature space

Table 8 presents the mean DCRS sub-score profiles by assigned pathway. The results reveal a consistent technical hierarchy across the three strategies.

Table 8. Mean technical attribute scores for each assigned circular pathway under the balanced scenario.

Assigned Pathway	BSS	TSS	RS	RFL
Recycle	0.487	0.860	0.079	0.582
Repair	0.575	0.607	0.320	0.667
Reuse	0.817	0.816	0.442	0.742

Devices assigned to the Reuse pathway exhibit the highest scores across all key indicators, with BSS at 0.817, RS at 0.442, and RFL at 0.742. This pattern confirms that devices in the best overall technical condition are systematically allocated to the highest-value recovery option. In contrast, Repair-assigned devices are primarily differentiated by moderate battery condition (BSS = 0.575), rather than by low repairability (RS = 0.320). This suggests that battery degradation constitutes the main technical constraint preventing these devices from being eligible for direct resale. Recycle-assigned devices display the lowest RS value (0.079) by a substantial margin, indicating that limited repairability is the defining characteristic of this group. Importantly, this does not coincide with poor performance in all dimensions, as evidenced by the relatively high TSS value (0.860). This implies that recycled devices are not necessarily technologically obsolete in terms of processing capability; rather, they are excluded from higher-value pathways due to insufficient repairability.

6. Conclusion

This study proposes an integrated framework for routing end-of-life smartphones to appropriate circular economy pathways by combining a Device Circularity Readiness Score (DCRS), a bi-objective NSGA-II optimization model, and TOPSIS-based solution selection. The framework addresses a key gap in the existing literature, where life cycle assessment studies typically quantify environmental impacts without generating device-level routing decisions, while reverse logistics models optimize network structures without explicitly incorporating device-specific technical conditions. By integrating both perspectives within a unified operational model, the study provides a bridge between environmental assessment and actionable decision-making.

The empirical findings indicate that technical device characteristics constitute the primary determinants of circularity outcomes. Sub-score analysis demonstrates that although technical specification scores (TSS) and battery health scores (BSS) remain relatively high across the dataset, the repairability score (RS) emerges as the most influential factor in routing decisions. Devices allocated to recycling are predominantly characterized by critically low repairability levels rather than insufficient processing capability. This result suggests that product design limitations and regulatory restrictions, rather than technological obsolescence, represent the principal barriers preventing smartphones from entering higher value pathways such as reuse and repair.

The optimization results reveal a strong inverse relationship between economic value recovery and CO₂ avoidance, with a Pearson correlation coefficient of -0.956. Nevertheless, the Pareto frontier remains relatively narrow, indicating that the second hand smartphone ecosystem is operating close to its structural efficiency boundary. This performance limitation arises because a substantial proportion of devices, approximately 34.4% in the balanced scenario, fail to meet the technical eligibility requirements and are therefore directly assigned to recycling. These findings demonstrate

that the proposed model effectively maximizes the potential of the existing device fleet within current physical and technical constraints.

Overall, the study shows that substantial improvements in circularity cannot be achieved solely through enhanced optimization techniques. Structural interventions at the policy and product design levels are also required, including extended spare part availability and the adoption of modular design standards. Future research may expand the framework to additional electronic products such as laptops and tablets while incorporating real time battery health data to improve model precision. Moreover, examining the effects of right to repair legislation could provide deeper insight into the potential evolution of economic and environmental trade offs within circular electronics systems.

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