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Review

Advancements in Plastic Waste Sorting: A Review of Techniques and Applications

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Abstract

The widespread utilization of plastic materials across various industrial sectors drives a continuous increase in global polymer demand. The exponential production growth generates severe environmental challenges regarding municipal solid waste management, as substantial fractions of post-consumer residuals enter landfills due to limited recycling infrastructure. Mitigating the global environmental burden requires the implementation of advanced recovery strategies to transition polymer waste into viable secondary feedstocks. Consequently, deploying efficient sorting techniques constitutes a fundamental requirement to integrate plastic materials into formal waste management protocols and optimize recycling yields. Technological innovations currently drive the transition from traditional manual segregation towards highly sophisticated automated sensor-based sorting architectures, maximizing separation efficiency. In this context, the present study comprehensively reviews pretreatment classification techniques engineered to fractionate heterogeneous waste streams into high-purity material flows. Rather than restricting the analysis to polyolefins, this review encompasses a broad spectrum of commodity polymers predominantly found in urban solid waste environments.

Keywords: polyolefins; circular economy; sensor-based separation; artificial intelligence; municipal solid waste management; polymer recovery

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1. Introduction

Annually, the world generates more than 2 billion tons of municipal solid waste (MSW), with production rates varying from less than 1 kg per capita per day in nations with low income to over 2 kg per capita per day in nations with high income [1]. Municipal solid waste typically comprises a mixture of materials characterized by a composition including plastics, glass, food scraps, yard trimmings, textiles, paper, and other waste, which pose challenges for recycling efforts [2–5]. Approximately 10% (numbers vary from 5% to 20%, depending on the investigated region and economic development) of the

waste consists of plastics, with the majority (about 60%) comprising polyolefins such as PE (polyethylene), HDPE (high-density polyethylene), LDPE (low-density polyethylene), LLDPE (linear low-density polyethylene), and PP (polypropylene). The remaining fraction includes PET (poly(ethylene terephthalate)), PVC (poly(vinyl chloride)), PS (polystyrene), and other polymers [6–8]. A portion of plastic waste originates from postindustrial sources or car scrap, which can be sorted [9].

Efforts have been dedicated to advancing plastic recycling methodologies, as evidenced by the many reviews available in the literature. For instance, the work by Sambyal et al. [10] explores mechanical and advanced chemical recycling strategies, including depolymerization and pyrolysis. The study highlights advancements, including strategies to mitigate thermomechanical degradation and the employment of compatibilizers to manage plastic blends during downstream processing. Concurrently, other investigations, like the one performed by Oyewale et al. [11], categorized pretreatment principles. These publications describe segregation mechanisms as functions of material properties, encompassing techniques that include magnetic separation, density-based sorting, and triboelectrostatic behavior. However, although these methods can be regarded as essential for proper waste processing, the isolated application of these methods cannot resolve the heterogeneity of waste streams.

To bridge the limitations and build upon the mechanisms, the literature highlights the role of technologies in achieving the appropriate purity thresholds for recycling. For instance, Lakhouit [12] underscores the integration of digital technologies based on artificial intelligence (AI) and the internet of things (IoT) to modernize waste sorting infrastructures. Particularly, the deployment of AI-powered computer vision, deep learning architectures, and robotic manipulators within material recovery facilities (MRFs) can facilitate the identification and fractionalization of waste streams. By automating these tasks, the systems enable a transition from manual sorting processes to the continuous sorting of waste compositions. Ultimately, the incorporation of these types of architecture can ensure the supply of feedstock with the quality demanded by downstream chemical transformations [13].

However, while these previously published works establish a theoretical basis for this subject, the literature has concentrated on downstream chemical transformations or examined the sorting operations as independent processes. Consequently, an area for development regards the real implementation of these technologies. As a matter of fact, the success of chemical and mechanical recycling techniques remains dependent on the purity of the feedstock. Therefore, addressing this requirement involves the analysis of integrated separation engineering, evaluating the hybridization of sorting architectures needed to yield streams on an industrial scale.

To bridge this gap and address the complexity of the recycling landscape, the present study extends previous analyses to industrial innovation by evaluating material separation technologies. The research explores the hybridization of mechanical, electromagnetic, gravitational, density-based, and wet techniques with sensor-based architectures. Specifically, the review consolidates strategies that integrate spectroscopic identification (FTIR, NIR) and active identification technologies with data processing systems (AI, chemometrics) to optimize the sorting ecosystem. By combining scientific knowledge with industrial realities, the present manuscript reviews the design of sorting architectures that are capable of meeting the purity demands of the circular economy and providing the plastic streams required to support a circular chemical chain. Finally, this survey incorporates an analysis of the industrial landscape, identifying market players and the tradeoffs of commercial solutions. To demonstrate the novelty and map the literature gap, a quantitative analysis of published review articles in the Web of Science database was conducted, the detailed methodology of which is presented in Section 2.

2. Methodology

An initial analysis collected published review articles in the Web of Science database. Using the keywords "sorting and polymer(s)", the search identified 227 review articles. The evaluation of the contents revealed that 19 papers presented subjects directly aligned with technical sorting engineering and manipulation of waste plastic streams. The majority of the publications addressed general recycling routes (mechanical, chemical, and thermal), whereas only a fraction focused on the hybridization of mechanical sorting with multisensory architectures, chemometrics, and artificial intelligence.

Following the initial analysis, the bibliometric review was executed leveraging the Web of Science database, employing the topics "plastic" AND "waste" AND "sorting" to establish the primary dataset. The search generated a data bank that comprised 833 papers. To ensure relevance, a multistage screening process was applied. The inclusion criteria required publications that focused on engineering applications, physical principles of separation processes, and sensor-based architectures (such as near-infrared, mid-infrared, Raman, and laser-induced breakdown spectroscopy). The exclusion criteria removed publications focused on macroscopic waste management policies, life cycle assessments, and landfill applications (which accounted for 144 isolated results).

The application of the criteria restricted the selection to the core studies. The sequence of the literature selection, encompassing the identification, screening, and eligibility phases, is quantitatively mapped in the process flow diagram (Figure S1, Supplementary Information). As depicted in the diagram, the identification phase established the primary dataset of 833 records from the Web of Science database. Following the initial retrieval, the screening phase applied the exclusion criteria, systematically removing publications aligned with macroscopic waste management policies, life cycle assessments, and landfill applications. The final reduction of studies relied on an inclusion criterion: the selected publications were required to investigate the physical mechanisms governing the sorting techniques and the integration of artificial intelligence for property detection (color, shape, size), rather than reporting performance metrics. The structured methodology ensures the retention of literature focused on engineering applications and multisensory architectures.

The analysis of the Web of Science categories revealed the multidisciplinary nature of research on sorting technologies. The dataset indicated a concentration of publications in domains including Chemistry (24.3%), Polymer Science (16.5%), and Materials Science (15.1%). The distribution highlights the intersection of chemical principles, material properties, and engineering applications. Furthermore, the presence of fields such as Nanoscience (8.7%) and Environmental Sciences (6.4%) corroborated the integration of disciplines required to develop sorting architectures.

Table 1 categorizes technologies from the selected literature into three functional domains: (i) physical-property-based separation; (ii) sensor-based sorting; and (iii) data processing and intelligent systems. The classification criteria reflect the operational hierarchy of automated sorting facilities. The first domain encompasses techniques that make use of density gradients and electromagnetic fields for mechanical separation. The second domain identifies spectroscopic methods and optical sensors for polymer characterization. The third domain captures the implementation of machine learning models to automate sensor output interpretation.

Table 1. Categorization of plastic waste sorting technologies into physical material separation, sensor-based identification, and intelligent data processing systems.

Material Separation Technologies	Sensor-Based Sorting	Data Processing and Intelligent Systems
Air separator	X-Ray Fluorescence (XRF)	Blockchain
Sink–float separation	Near-infrared spectroscopy (NIR)	Artificial intelligence
Hydrocyclone	Raman Spectroscopy (Raman)	Chemometric
Jigging	Laser-Induced Breakdown Spectroscopy (LIBS)	-
Selective dissolution	Hyperspectral imaging (HSI)	-
Triboelectrostatic	-	-
Magnetic Density Separation	-	-

To capture the industrial landscape, a complementary patent analysis was performed using the WIPO, Google Patents, and Espacenet databases. Employing the keywords "plastic" AND "waste" AND "sorting" within the title and abstract fields yielded 1285 patent applications in the WIPO database and 1374 applications in the Espacenet database. Following a filtration process based on technical claims, relevance to engineering applications, and redundancy reduction, a set of patents published between 1992 and January 2026 was selected for evaluation. Tables S1 and S2 (Supplementary Information) summarize the patent applications related to plastic waste sorting. The table details the publication numbers, titles, publication dates, and technological focus of the inventions. Extracting the variables enables the mapping of industrial trends, identifying shifts from mechanical configurations to data-driven classification systems.

The comparative analysis of the bibliometric data (Table 1) and the patent landscape (Tables S1 and S2) reveal a distinction in the evolution of sorting technologies. While the academic literature focuses on the isolated characterization of unit operations (investigating density separation or spectral signatures independently, for instance), the intellectual property data unveils an industrial trajectory towards process hybridization and digitalization [12]. The cross-reference of the data sources highlights an alignment in the integration of artificial intelligence and reveals a divergence in application focus. While academic publications prioritize classification models, patent claims emphasize throughput integration and adaptability to variations in waste streams. The patent landscape (2020 to 2026) indicates a shift from passive separation to active systems that are capable of distinguishing food-grade materials and black plastics.

In this context, NIR spectroscopy encounters practical limitations associated with black plastics due to carbon black absorption and the distinction between food-grade and non-food-grade packaging [14]. Patent applications by entities such as Magnomer and Digimarc address these limitations through the introduction of chemical tracers, fluorescent markers, and digital watermarking [15,16]. Rather than improving the sensitivity of the sensor, the industry modifies the packaging to communicate the composition to the sorting line, enabling the recovery of food-grade polypropylene and polyethylene [17].

The integration of artificial intelligence constitutes a pillar of industrial innovation that has been largely absent in earlier academic reviews. While prior studies explored chemometrics, industrial developments utilize deep learning and computer vision to classify waste based on object morphology and texture [18]. The patent data from companies like Sortera Technologies and Recycleye indicate that combining Medium Wave Infrared cameras with neural networks can even allow the sorting of dark materials and composites.

The analysis proposed here also highlights the synergy between mechanical sorting and chemical recycling. A subset of the identified patents focuses on the purification of

feedstock for pyrolysis and gasification. Unlike the production of mechanically recycled streams, the preparation for chemical recycling prioritizes the removal of catalytic poisons such as halogens, metals, and moisture. The intellectual property landscape suggests that future sorting facilities will operate as hybrid systems, producing distinct streams for mechanical reprocessing and chemical depolymerization.

Finally, industrial research and development is driven by the necessity to meet regulatory targets, such as the minimum content of post-consumer recycled material in packaging. The focus on high throughput and automated quality control observed in the patent documents reflects the pressure to reduce operational costs and reliance on manual sorting. Consequently, the academic sector benefits from aligning future research with the industrial challenges, particularly in developing sensors for tracer detection and optimizing AI algorithms for waste characterization.

3. Material Separation Technologies

Solid waste treatment plants receive mixtures of domestic and industrial wastes, frequently collected without prior segregation. The waste streams contain cardboard, styrofoam, metallic materials, nonmetallic materials, and organic matter [19]. To optimize operations, preliminary sorting technologies act to concentrate the input stream, aiming to separate organic fractions from recyclable polymers. Methods deployed to isolate inorganic fractions include magnetic separators for ferrous metals and eddy current separators for nonferrous metals [13,20]. Following the preliminary steps, plastic sorting technologies encompass physical processes and mechanical equipment designed to isolate specific polymer types. The physical systems involve gravity separation, air separation, electrostatic separation, and magnetic density separation [3,20]. The operational characteristics of the physical separation techniques are summarized in Table S2. While separation techniques contribute to polymer recovery, industrial implementation reveals operational limitations. Physical separation systems face bottlenecks when processing composite packaging, overlapping densities, and highly contaminated items [21]. Consequently, isolated unit operations struggle to achieve the purity targets demanded by downstream chemical recycling, requiring the hybridization of mechanical sorting with sensor-driven architectures.

3.1. Pre-Sorting Techniques

Preliminary plastic sorting operations constitute methods deployed to partition polymeric materials into defined categories prior to downstream processing. Segregating polymers isolates specific material flows, mitigating contamination and adjusting the input stream. Preliminary sorting strategies encompass classification by color, morphology, dimensional properties, and chemical composition [3,22]. Standard preliminary unit operations include:

- Source separation: involves partitioning plastic waste at the generation point, including residences or industrial facilities. The operation relies on designated receptacles for specific polymer types. While conceptually advantageous, source segregation faces logistical bottlenecks and relies heavily on continuous public compliance.
- Manual sorting: depends on visual inspection and handpicking based on physical characteristics and product markings. Human intervention occurs at material recovery facilities or generation points. Industrial scalability remains constrained by elevated labor costs, restricted throughput rates, and human error during sustained operation shifts.
- Size reduction: encompasses shredding or granulating operations to alter the particle size distribution of the waste stream, standardizing dimensions for subsequent mechanical handling.

- Magnetic separation: utilizes magnetic fields to extract ferrous metal contaminants from the bulk plastic flow.
- Air classification: employs pressurized pneumatic streams to fractionate materials based on aerodynamic profiles. Aerodynamic drag entrains low-density fractions, whereas high-density components settle into collection vessels.

Pretreatment technologies execute the initial fractionation of municipal solid waste, targeting the extraction of incompatible materials, including ferrous and nonferrous metals, from the polymer recycling lines. During the initial stage, organic fractions require isolation from the dry recyclables utilizing trommels, which operate as rotating tubular screens for dimensional classification. Following organic matter extraction, recyclable polymers undergo comminution to generate flakes, adjusting the material format for subsequent crushing stages [13]. Industrial equipment deployed for municipal solid waste comminution includes swing hammer shredders, rotating drums, alligator shears, hammer mills, ring mills, shear shredders, and impact crushers [13]. While mandatory for material liberation, comminution processes introduce operational challenges by generating fine particulates and dust, which interfere with downstream optical sensors. Furthermore, size classification units face throughput limitations, as flexible packaging and plastic films frequently blind the screening surfaces, demanding frequent maintenance interventions. Figure 1 illustrates the sequential arrangement of mechanical separation technologies within an integrated sorting chain. Each unit operation fulfills a specific preconditioning requirement to optimize downstream efficiency. Trommel screens execute size exclusion to remove fine contaminants, while magnetic and eddy current separators eliminate metallic fractions that interfere with optical sensors. Ballistic separators and air classifiers provide density-based and shape-based segregation, establishing the material singulation necessary for accurate sensor-based identification.

3.1.1. Rotating Screening Machine or Screw Press (Trommel)

In municipal waste treatment, the rotating screening machine (trommel) compresses organic fractions through narrow slits, separating soft, moisture-laden components (biomass). The screening operation fractionates waste mixtures, including biomass, plastics, paper, wood, animal bones, and metal, into size categories, utilizing a cylindrical surface composed of successive sections with different aperture sizes [23]. Figure 1A shows a schematic illustration of the rotating screening. The mixed waste is fed into the trommel through a conveyor belt and separated by size, generating a permeate stream (smaller particles, including wet organic mass) and a retentate stream (larger particles directed to subsequent units). Trommel performance depends on geometrical and operational variables, including cylinder length, diameter, screen mesh size, angle of slope, rotational speed, and mass flow rate [23,24]. The rotational speed dictates the particulate motion mechanism within the cylinder, transitioning from slumping at low speeds to cataracting at intermediate speeds, and eventually to centrifuging at increased speeds. Target size separation occurs during the cataracting phase, whereas centrifuging forces particles against the cylinder wall, reducing screening capability [23]. Industrially, trommels experience operational limitations due to the entanglement of flexible plastic films and textiles, which block the screen apertures and reduce throughput. Additionally, moisture exacerbates the adhesion of organic matter to recyclable polymers, causing downstream cross-contamination. To mitigate the operational bottlenecks, facilities integrate upstream bag openers to restrict material dimensions prior to screening, combined with external rotary brushes to continuously clear the apertures [13,25]. Furthermore, addressing moisture challenges requires preconditioning steps, including biological drying or the implementation of downstream friction washers to detach organic contaminants from polymer surfaces [19,26].

3.1.2. Disc Screen

In municipal waste treatment, the disc screen constitutes a mechanical operation for extracting organic waste fractions from recyclable materials. Figure 1B presents a schematic representation of the disc screening operation. Inside the chamber, an array of uniformly spaced rotating discs separates the biomass. Smaller and denser biomass components fall through the gaps between the rotating discs, whereas larger fractions are directed toward the periphery of the assembly [27]. While disc screens process material flows, the mechanical configuration is susceptible to wrapping. Flexible polymers, tapes, and textiles wrap around the rotating shafts, requiring periodic machine shutdowns for manual cleaning and maintenance. To mitigate the operational limitations, facilities implement anti-wrapping shaft designs or substitute the screening equipment with ballistic separators when processing streams with elevated concentrations of two-dimensional flexible packaging [28].

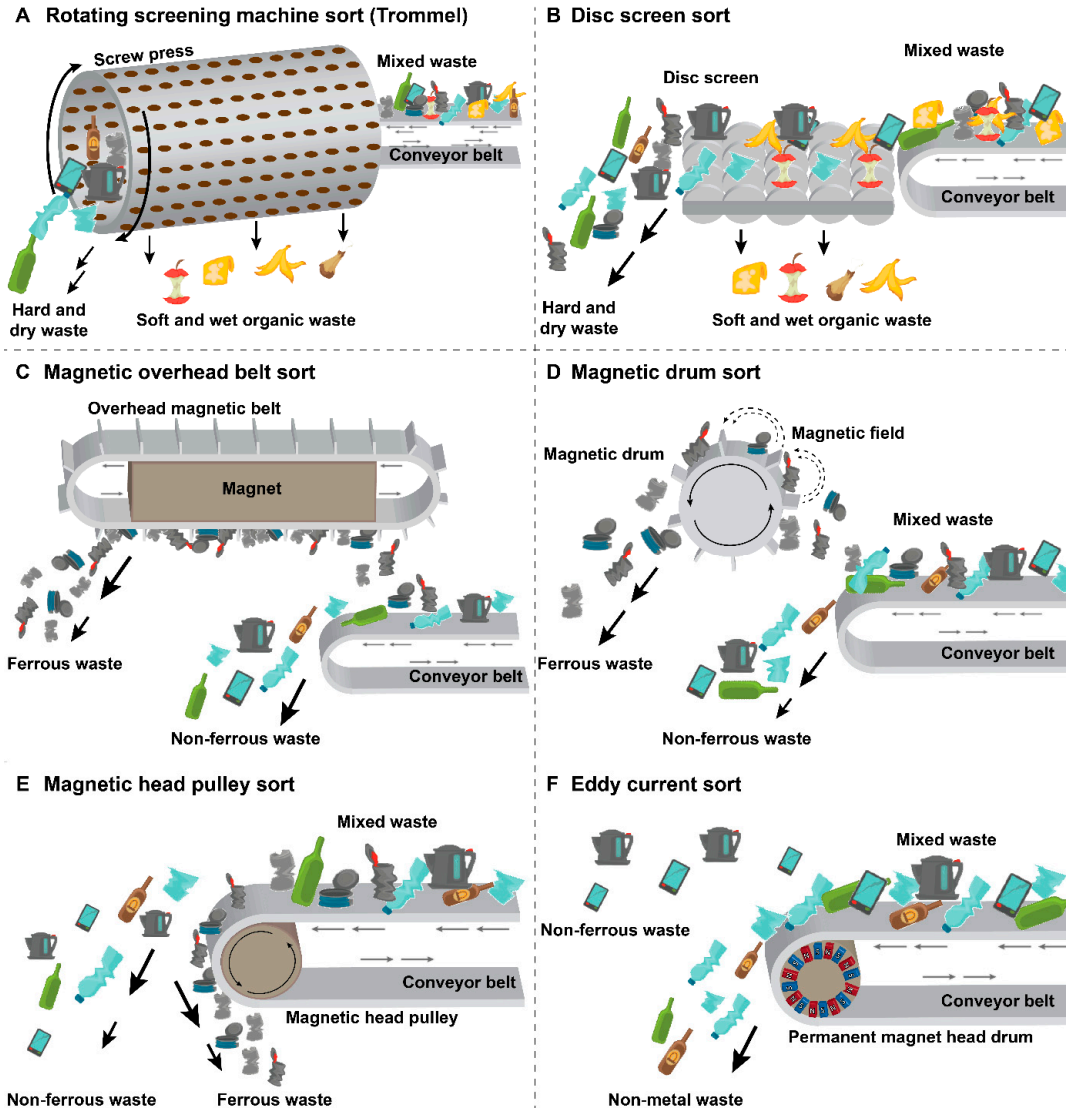


Figure 1. Schematic representation of conventional mechanical pretreatment and material recovery technologies. The panels illustrate size classification units—(**A**) rotating screening (trommel) and (**B**) disc screening—followed by ferrous metal recovery systems—(**C**) magnetic overhead belt, (**D**) magnetic drum, and (**E**) magnetic head pulley; nonferrous metal removal via (**F**) eddy current separation. Solid and dotted arrows indicate the directional flow within the sorting process.

3.1.3. Magnetic Techniques

Metal objects constitute a fraction of municipal solid waste, with concentrations varying between 5% and 15% [27]. Ferrous waste fractions can be segregated from mixed waste streams with magnetic techniques based on magnetic susceptibility. Magnetic-based techniques separate ferromagnetic metals, including iron and steel, from polymers and nonferrous metals.

The magnetic overhead belt imposes a magnetic field across the direction of the mixed waste flow. Through the application of a magnetic force, ferrous metal pieces are lifted against gravity and extracted from the underlying waste layer. A separation drum retains the recovered metals against a moving belt, discharging the material into a secondary stream (Figure 1C) [20]. The remaining waste, including polymers, continues to flow forward. Overhead belts experience operational limitations when processing deep material layers, requiring preliminary waste distribution to prevent the entrapment of plastics beneath heavy metallic items.

The extraction of ferrous fractions from mixed waste streams is alternatively performed using a magnetic drum separator, which consists of a stationary permanent magnetic assembly covering half of the drum circumference. Upon introduction of the waste, the magnetic field attracts ferromagnetic materials against the rotating shell. Nonmagnetic materials fall freely following a ballistic trajectory. The shell transports the ferrous components out of the magnetic zone to a discharge area, where the materials drop into specific bins (Figure 1D) [29].

Additionally, mixed waste is conveyed through a magnetic material handling system, utilizing a conveyor belt operated with a magnetic head pulley that can replace the standard discharge pulley. The magnetic field seizes the ferromagnetic waste components, causing the metals to adhere to the belt and travel underneath the pulley before releasing. Nonferromagnetic fractions discharge in a parabolic trajectory, as illustrated in Figure 1E [20]. The equipment units operate as a pretreatment stage before the eddy current separators to isolate ferrous metals, preventing mechanical damage to downstream equipment.

The segregation process employs eddy current separators to recover nonferrous metals, utilizing a rotary drum equipped with neodymium magnets (NdFeB) arranged with alternating north and south poles. A mixture containing nonferrous metal fractions and nonmetallic waste is conveyed towards the rotary drum. The rapidly alternating magnetic field induces electrical currents within the conductive particles, generating an opposing magnetic field. The interaction creates a repulsive Lorentz force, ejecting nonmagnetic electrically conductive metal fractions from the waste stream (Figure 1F). Despite isolating aluminum and copper from polymers, eddy current separators present industrial limitations. The technique exhibits reduced recovery rates for particles smaller than 5 mm due to weak repulsive forces. Furthermore, specific metals heat rapidly within the eddy current field, creating thermal risks that damage the separator belt and surrounding polymer fractions [3,13].

3.2. Mechanical Techniques

Mechanical separation techniques can be classified as wet and dry operations based on the sorting medium.

3.2.1. Dry Techniques

Air-Based Separation

Air-based classifiers utilize aerodynamic drag to separate low-density materials from high-density fractions. A compressed-air nozzle releases a high-pressure air jet, imparting a separation force on the mixed waste sample. The pneumatic classification techniques

comprise three categories: (i) gravity air separation, (ii) ballistic separation, and (iii) air table separation, as shown in Figure 2 [30].

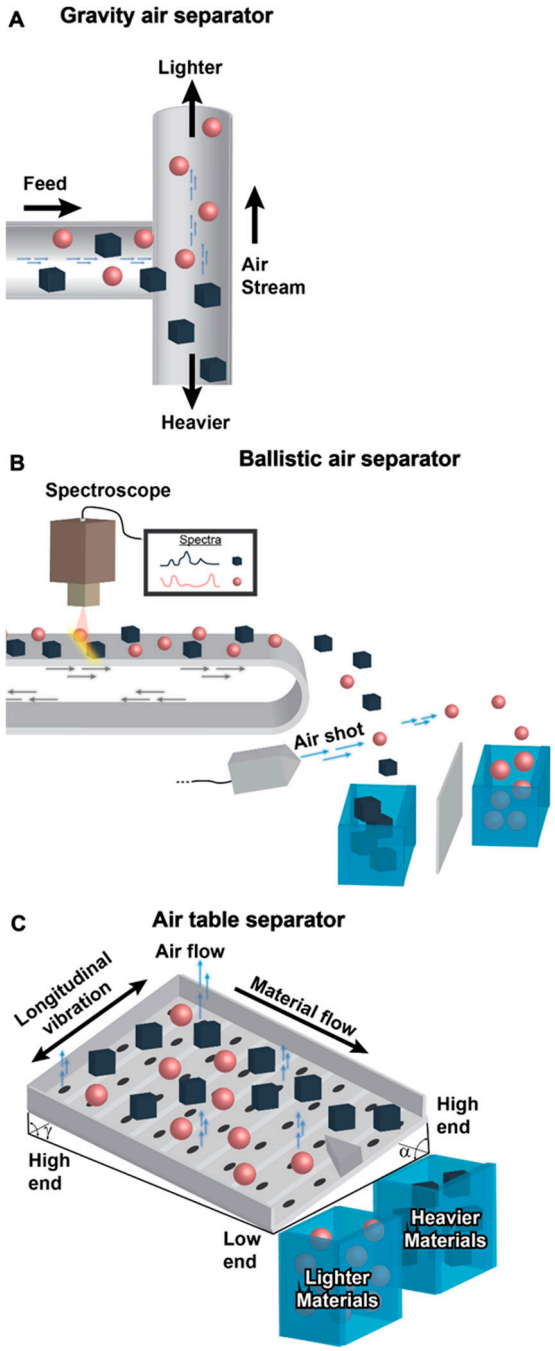


Figure 2. Schematic illustration of dry density separation technologies relying on density and shape differences: gravity separator (**A**), ballistic separator (**B**), and air table separator (**C**). Solid arrows indicate the directional flow within the sorting process.

Gravity air separation (Figure 2A) operates based on terminal settling velocities. The plastic stream flows into a vertical column, where an upward air current entrains lightweight objects, while higher-density objects overcome the aerodynamic drag and fall due to gravity. Furthermore, gravity separators are occasionally integrated with electrostatic or magnetic fields to extract specific contaminants and adjust the stream composition [3,30].

The ballistic air separator (Figure 2B) operates in conjunction with spectroscopic techniques. The waste material is identified by a spectrometer, including a near-infrared

spectrometer. Following polymer identification, a processing unit transmits a signal to a compressed-air manifold, releasing a high-pressure air jet that deflects the targeted material into a designated container [13,31].

The air table separator (Figure 2C) operates as a density-based aerodynamic sorting mechanism. By introducing an upward continuous air flow through a vibrating porous deck, the equipment stratifies mixed waste streams based on specific mass and aerodynamic behavior. Heavy contaminants settle and migrate upwards along the deck vibration, whereas lightweight polymer fractions are fluidized and discharged at the lower elevation [20,30]. While historical literature [32] frequently claimed high-purity segregation capabilities for the specific technique, current industrial operations establish that air tables function predominantly as preliminary mechanical conditioning units. Modern multicomponent waste streams exhibit severe density overlaps among distinct commodity polymers, drastically reducing the final separation efficiency of strictly aerodynamic methods. Consequently, modern material recovery facilities utilize air table equipment primarily to execute bulk fractionation, efficiently isolating paper and 2D flexible films from 3D rigid plastics, prior to routing the material flow toward highly accurate downstream sensor-based optical separators. Integration ensures that downstream optical units receive a uniform material feed, ultimately achieving the strict high-purity metrics demanded by contemporary circular economy frameworks [33].

General pneumatic separation techniques sort various components, including polymers, films, paper, cardboard, textiles, and three-dimensional plastic containers. Separation efficiency correlates well with the density differences among the sorted materials [34]. Parameters including particle size, shape, and morphology affect aerodynamic drag and overall performance [20,30]. To mitigate morphological variations, mechanical milling standardizes particle size and structure, allowing the separation to be governed primarily by specific mass.

The industrial application of ballistic and air separation is corroborated by recent patent filings. The patent disclosures propose integrated systems that sequentially process two-dimensional flexible polyolefin fragments and three-dimensional rolling materials prior to optical sorting steps, increasing the purity of the final fractions [35,36].

Air separation techniques are widely implemented in material recovery facilities due to the reliance on aerodynamic principles and the capacity to process diverse material streams. Among the pneumatic variants, sensor-activated ballistic air ejection provides selectivity rates exceeding 90% under optimized conditions [30]. The operational metrics explain the presence of multiple industrial suppliers in the market, including Stadler, Tomra, Amut, Marcovil, and Bianna.

Triboelectric Separation

Triboelectric separation utilizes electrostatic properties to segregate polymer types. The operation, illustrated in Figure 3, involves fractionating milled plastic particles within a rotating drum to generate surface electrostatic charges [37]. The charged particles fall through an electrostatic field established by two opposing electrodes. A positive electrode attracts negatively charged polymers, whereas a negative electrode attracts positively charged polymers. The trajectory of the falling particles diverges due to attractive and repulsive electrostatic forces, influenced by particle mass, size, and accumulated charge [20,30,38–41]. The fundamental triboelectric charging sequence follows the order: (+) PMMA > ABS > PC > PS > PET > HDPE > LDPE > PP > PVC > PTFE (−) [20,30,38–41].

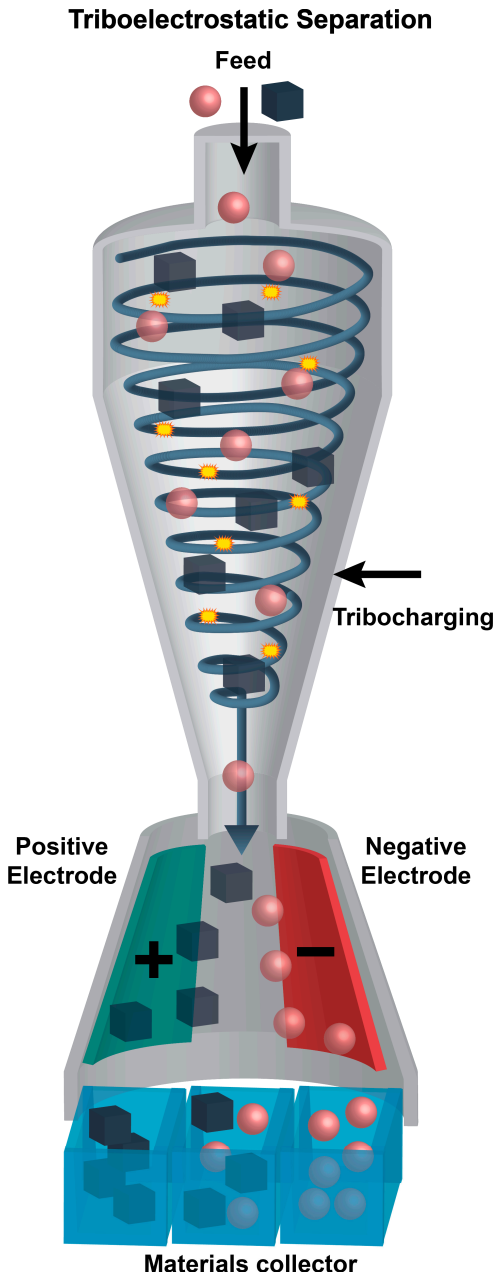


Figure 3. Schematic representation of the triboelectric separation process, illustrating the frictional charging of milled plastic particles and their subsequent trajectory-based segregation within an electrostatic field. The burst symbols illustrate the friction between the materials, which generates static electricity for the tribocharging process.

Despite the theoretical viability of triboelectrostatic separation, executing precise polymer segregation in industrial environments requires mitigating severe operational variabilities. The standard triboelectric charging sequence assumes that pristine polymer surfaces can interact under highly controlled atmospheric conditions. However, the current literature has established that the effective work function and resulting charge polarity of post-consumer plastics fluctuate significantly based on external environmental factors [38]. Relative humidity constitutes a primary operational variable, as elevated moisture levels facilitate the formation of conductive aqueous surface layers. The conductive films prematurely dissipate the accumulated electrostatic charge, drastically reducing the final separation efficiency [42]. Furthermore, the physical surface condition of the polymer dictates the triboelectric response. Chemical oxidation, thermal degradation, and adhered

organic residues alter surface electron transfer kinetics, demanding rigorous pretreatment protocols, including mechanical washing and controlled drying, to stabilize unpredictable charging behaviors that deviate from standard reference tables [30,41]. Finally, the specific composition of contact materials utilized within the friction charger (including aluminum, copper, or stainless-steel walls) dictates the absolute magnitude of the generated surface charge, as particle–wall interactions frequently dominate over particle–particle friction [13].

Consequently, scaling triboelectrostatic architectures for municipal solid waste processing mandates dynamic process calibration to compensate for continuous fluctuations in material humidity, surface contamination, and mechanical wear of internal charging components. To further optimize the charging mechanisms, particle dimensions must be standardized via mechanical milling, targeting an optimal range of 2.0 mm to 4.0 mm [30,41]. Conversely, overmilling generates fine polymeric dust, which exacerbates charge dissipation, induces the agglomeration of identical particles, and increases adhesion to the charger walls, ultimately reducing high-speed throughput and increasing specific energy consumption [13].

The charging mechanism is categorized into solid single-phase and gas–solid two-phase configurations. The solid single-phase system relies on mechanical friction among solid particles, utilizing rotating tubes, rotary blades, and vibrating conveyors. Alternatively, gas–solid two-phase systems employ pneumatic interactions to charge the mixed solid particles, utilizing cyclones, fluidized beds, and propeller-type tribochargers [13].

Triboelectric separation achieves targeted recovery rates operating without water or dense media. The method segregates polyolefins, including PE and PP, from PVC, PET, ABS, and biodegradable polymers like PLA, PCL, and PHBV [43]. Commercial equipment suppliers include Stadler, Alicontrols, and Prodecologia. Despite avoiding liquid media, the operation presents a substantial energetic footprint, with specific energy consumption reaching 31 kWh per ton, primarily driven by the requisite upstream mechanical milling and rigorous controlled drying stages [40,44].

3.2.2. Wet Techniques

Sink–Float Separation

Density separation segregates polymer types based on differences in specific mass. The operation, illustrated in Figure 4, involves immersing a plastic mixture into a liquid medium. Water, presenting a standard density of 1.0 g cm^{-3}, serves as the primary fluid to separate light polyolefins from heavy polymers. The aqueous medium isolates PET (1.38 g cm^{-3}) and PLA (1.24 g cm^{-3}) from the lighter HDPE (0.93–0.97 g cm^{-3}), LDPE (0.91–0.94 g cm^{-3}), and PP (0.89–0.92 g cm^{-3}). The initial immersion stage concurrently functions as a preliminary washing step, detaching paper labels and organic residues from the polymer surfaces [13,30,37].

Despite isolating polyolefins from heavy plastics, static density separation exhibits industrial limitations when processing materials with overlapping specific masses. Segregating HDPE from LDPE utilizing exclusively static fluid baths yields compromised purity rates. Density ranges overlap, and parameters like surface wettability, trapped air bubbles, and morphological variations modify the apparent specific mass of the flakes. To resolve operational limitations and fractionate the polyolefin stream, facilities must modify fluid density utilizing targeted aqueous solutions of inorganic salts or alcohols. Alternatively, the industry implements centrifugal dynamic separation, utilizing hydrocyclones to amplify discrete density differences through high gravitational forces [3,9,44,45].

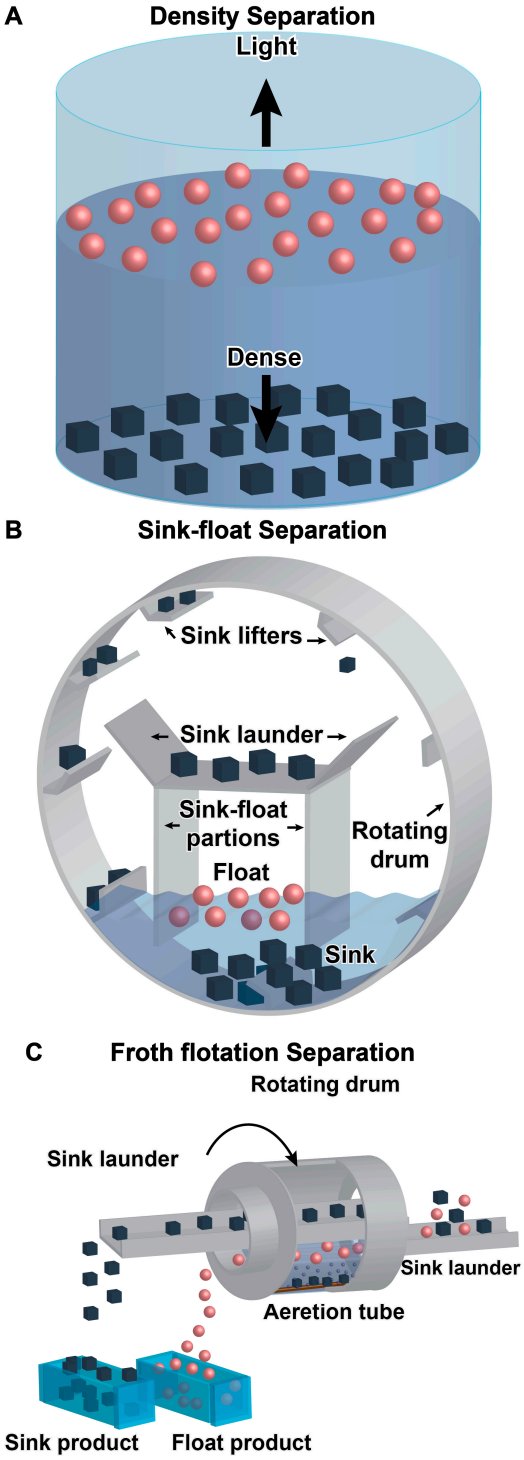


Figure 4. Schematic illustration of density separation principles (**A**); sink–float (**B**) and froth floatation (**C**) separation processes. Schematic representation of wet density separation techniques, illustrating the sink and float method in longitudinal (**A**) and rotatory (**B**) tanks, as well as the froth flotation (**C**).

Facilities implement two distinct mechanical configurations: sink–float separation and froth-flotation. Sink–float equipment comprises longitudinal tanks (Figure 4A) or rotatory tanks (Figure 4B). Mixed streams enter the tank; low-density flakes float to the surface for collection via a rotary drum, while high-density flakes sink to the bottom and are discharged to a downstream collector. Conversely, froth flotation exploits polymer hydrophobicity and surface tension. Gaseous bubbles adhere to specific hydrophobic particles, carrying targeted material to the surface of the flotation apparatus (Figure 4C) [40,41,43,46].

Sink–float separation processes diverse polymer streams. Commercial equipment suppliers include Amut, ASG, Eastman Chemical Company, Nippon Kokkan, and United Resources Recovery Corporation. The mechanical operation requires a specific energy input equivalent to 24 kWh per ton. To address operational challenges, recent 2025 patent disclosures propose stratification apparatuses equipped with real-time specific gravity control and automated feedback loops. Industrial innovations aim to stabilize fluid density and optimize the recovery of target polymers from heterogeneous waste mixtures [20,32,38,47,48].

Despite the high-density resolution achieved by wet separation techniques, including sink–float tanks and froth flotation cells, the extensive water footprint creates severe environmental and economic bottlenecks. Industrial operations processing municipal solid waste consume between 2.0 and 5.0 cubic meters of water per ton of sorted plastic material, depending directly on the baseline contamination level of the initial input stream. Furthermore, dynamic wastewater treatment protocols are strictly mandatory, as the continuous sorting process generates complex industrial effluents. The process water rapidly accumulates high biochemical oxygen demand (BOD), suspended microplastics, residual chemical reagents (specifically frothers and surface modifiers), and leached heavy metals originating from printed polymer labels. Implementing closed-loop water recirculation systems and rigorous effluent purification protocols significantly increases overall capital expenditures (CAPEX) and operational expenditures (OPEX). Current technoeconomic assessments indicate that comprehensive wastewater management accounts for 20% to 30% of the total processing costs. Consequently, the high financial burden associated with effluent treatment drastically reduces the commercial competitiveness of wet architectures when compared to modern dry sensor-based alternatives, driving the current industrial trend toward strictly pneumatic and optical sorting layouts [49].

Hydrocyclone

Hydrocyclone equipment fractionates plastic particles based on specific gravity within a centrifugal force field. The operation, illustrated in Figure 5, involves suspending shredded plastic flakes in an aqueous slurry and feeding the suspension tangentially into the hydrocyclone chamber. The tangential injection generates rapid rotational fluid motion, creating a primary descending vortex. Centrifugal acceleration forces high-density particles toward the conical wall, where the material spirals downward to discharge through the underflow apex. Conversely, low-density particles migrate towards the central low-pressure core, forming a secondary ascending vortex that exits through the overflow vortex finder at the top of the chamber [20,32,37,38,50].

Hydrocyclone performance depends strictly on fluid dynamic parameters, including the water-to-solid feed ratio, particle morphology, surface wettability, liquid viscosity, and the geometrical design of the separation chamber. Productivity experiences limitations tied to feed composition; excessive solids concentration induces physical clogging at the apex and alters the apparent fluid viscosity, hindering centrifugal segregation. Furthermore, particle size fundamentally dictates the separation efficiency. Minute particles experience predominant fluid drag forces that overcome centrifugal forces, causing fine high-density contaminants to incorrectly report to the light overflow fraction. Conversely, irregularly shaped flakes disrupt internal vortex stability, generating localized turbulence that mixes the segregated streams. Consequently, facilities must rigorously control the particle size distribution through upstream milling to match the specific hydrocyclone geometry, including cone diameter and length, which govern internal pressure drops and operational flow rates [13,30,50].

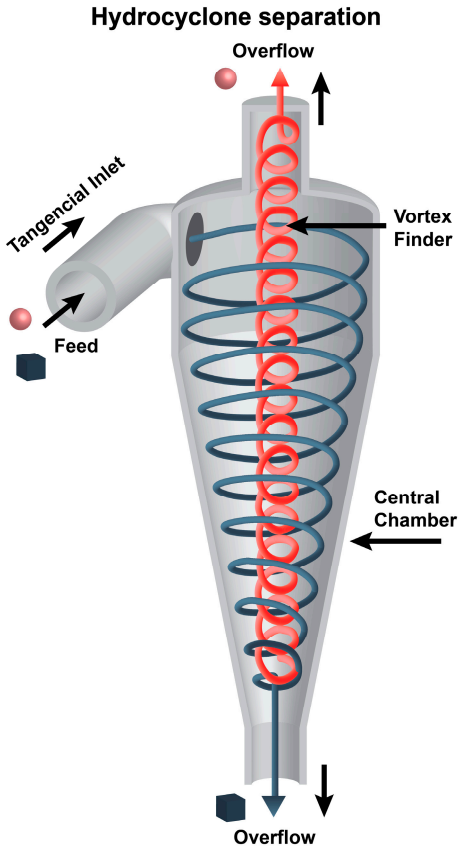


Figure 5. The hydrocyclone separation mechanism applied to plastic waste sorting, displaying the centrifugal trajectory of particles according to their density. Arrows indicate the directional flow within the sorting process.

Centrifugal separation achieves elevated purity grades for polymers presenting distinct specific masses. However, performance decreases when processing polymer blends with overlapping densities, notably mixtures containing PBST (1.35 g cm^{-3}) and PET (1.35–1.40 g cm^{-3}). Commercial equipment was supplied by suppliers such as Pla.to and Eastman Chemical Company. While resolving the static limitations of gravity tanks, the dynamic operation imposes specific energy consumption penalties. The specific energy required to pressurize the slurry and maintain the centrifugal vortex reaches 74 kWh per ton, representing a threefold increase compared to static density baths [9,43,51].

Jigging

Jigging constitutes a dynamic hydrodynamic separation technique adapted for polymer sorting based on specific mass variations. The operation, illustrated in Figure 6A, processes plastic waste through aqueous tanks equipped with mechanical pulsators. Mechanical pulsation induces periodic vertical fluid velocity, fluidizing the plastic slurry and stratifying the particles based on differential settling velocities and specific gravity [46]. As the feed flows across the jig bed, high-density particles penetrate the fluidized bed and settle as a concentrate at the bottom, whereas low-density particles remain in the upper strata and are discharged with the superficial fluid flow. Stratification relies on the interplay among buoyancy, hydrodynamic drag, gravitational forces, and the oscillatory motion of the fluid bed [50,52].

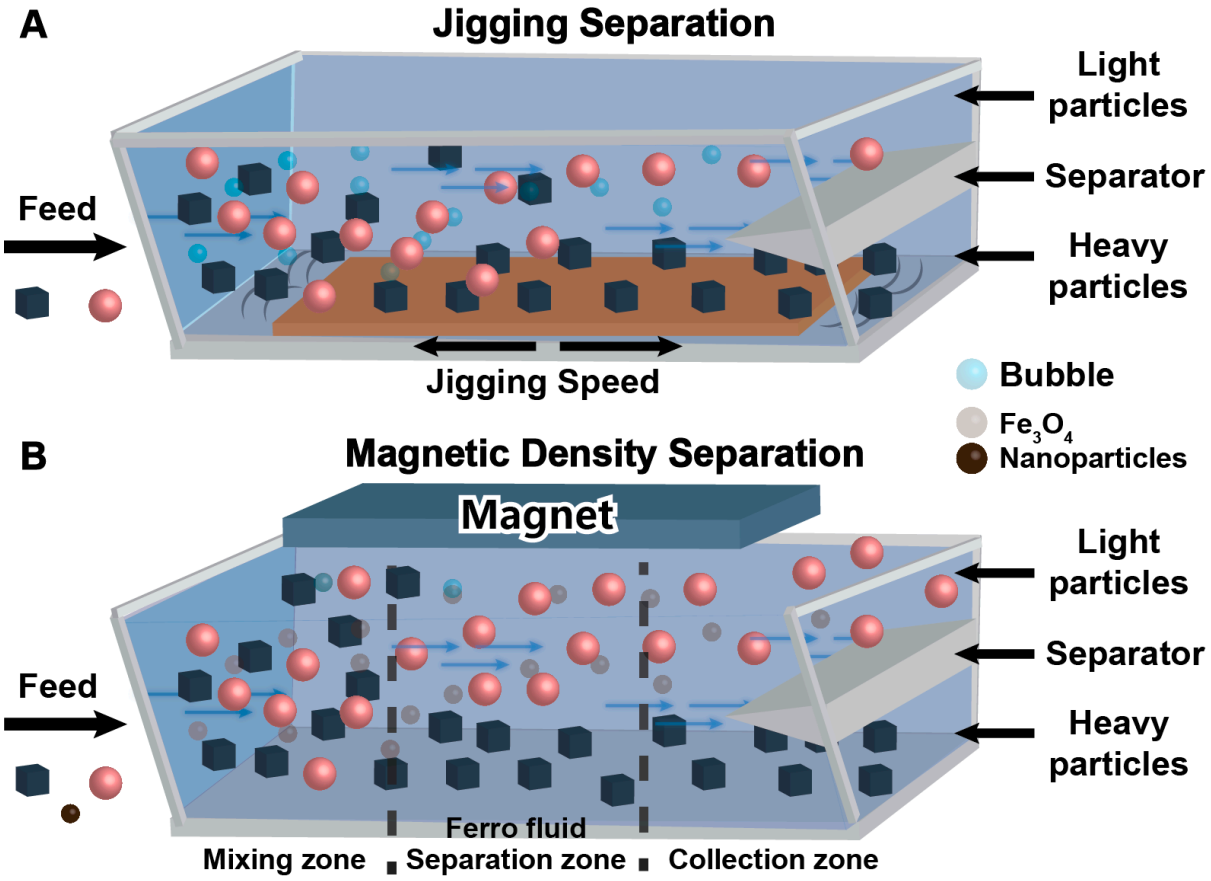


Figure 6. Schematic illustration of the jigging separation process driven by oscillatory fluidization and gravity settling (**A**) and the magnetic density separation apparatus employing nanoparticles to manipulate the apparent specific gravity of the plastic fractions (**B**). Arrows indicate the directional flow within the sorting process.

Stratification performance correlates directly with particulate characteristics, including size, morphology, and specific mass distribution, and with operational parameters like pulsation amplitude, stroke frequency, water flow rate, and bed depth. Conventional jigging encounters limitations when processing polymers with marginal density differences. To mitigate operational bottlenecks, facilities implement modified bubble jigging configurations, introducing controlled air dispersion into the separation chamber [52,53].

Jigging segregates heavy polymer fractions, isolating PVC, PET, PS, and ABS. Furthermore, the integration of bubble jigging expands the operational capability to fractionate polyolefins, including PP and HDPE. Entities supplying commercial or pilot-scale equipment include the University of Beijing, CVP Clean Value Plastics, and R&E. Despite the mechanical robustness, the wet operation imposes severe industrial constraints. The technique demands massive water volumes to maintain continuous bed fluidization, generating substantial wastewater streams that demand rigorous purification protocols. Additionally, the recovered polymer fractions emerge completely saturated, demanding downstream drying steps that significantly increase the overall specific energy consumption of the material recovery facility [13].

Magnetic Density Separation

Magnetic density separation utilizes a magnetizable fluid medium to establish a vertical density gradient, enabling the fractionation of polymer mixtures in a single continuous stage. The operation, illustrated in Figure 6B, utilizes an aqueous suspension of magnetic nanoparticles, typically iron oxide (Fe_3O_4). The mechanical configuration comprises a mix-

ing zone, a separation zone, and a collection zone. Initially, the mixing zone homogenizes the polymer feed and the nanoparticle suspension under a turbulent flow field. Within the separation zone, an external magnetic field is applied above the tank. The magnetic field attracts the nanoparticles, generating an upward magnetic force that opposes gravity. The interaction induces an artificial density gradient within the fluid, altering the apparent buoyancy of the suspended polymer particles. Separation performance relies on magnetic field intensity, fluid flow rate, polymer morphology, and the intrinsic magnetic properties of the nanoparticles [20,37,44,54].

While creating customizable density profiles, the technique encounters severe operational limitations when processing polymers with overlapping specific masses. The system fails to consistently segregate polyolefins, including PP (0.90–0.92 g cm^{-3}) and PE (0.88–0.96 g cm^{-3}), when mixed with heavy fractions like PET (1.35–1.40 g cm^{-3}), PVC (1.38 g cm^{-3}), and rubber (1.34 g cm^{-3}). Due to the complexity of the operation, commercial implementation remains restricted, with Liquisort functioning as the primary equipment supplier. Industrially, magnetic density separation can impose substantial economic and environmental constraints. The process requires continuous dosing of magnetic nanoparticles and massive solvent volumes. Furthermore, the recovery of the nanoparticles from the wastewater stream constitutes a critical technological bottleneck. Incomplete nanoparticle recovery leads to material loss and effluent contamination, while the recovered polymer fractions require intensive downstream washing and thermal drying to remove residual iron oxide [20,37,44,54].

Despite the innovative physical approach of magnetic density separation, the economic viability of the entire sorting process relies on the efficient continuous recovery of the suspended magnetic nanoparticles. Current technological limits reveal that a continuous volume loss of nanoparticles occurs during standard industrial operations due to mechanical adhesion to the sorted polymer surfaces and incomplete magnetic flocculation within downstream rinsing stages [55]. The continuous depletion of iron oxide particles inflates overall operational expenditures, as synthesizing and replenishing the superparamagnetic material constitutes an expensive requirement. To mitigate the severe financial burden, material recovery facilities must implement a multi-stage magnetic recovery circuit, utilizing high-gradient magnetic separators to extract and recirculate the nanoparticles from the washing effluents [55,56]. However, achieving nanoparticle recovery rates exceeding 99% is a prerequisite to sustain long-term commercial competitiveness, which can constitute a formidable technological challenge [27,55]. Consequently, the high initial capital expenditures associated with constructing closed-loop fluid recovery infrastructure currently restrict the widespread industrial implementation of the specific sorting architecture.

Selective Dissolution

Selective dissolution fractionates polymer blends based on differential thermodynamic solubility, requiring rigorous control of operational temperature and solvent selection. Thermodynamic affinity between the solvent and the target polymer dictates the separation driving force, while solvent diffusivity through the polymer matrix governs the mass transfer rate and subsequent equipment sizing. Selective extraction isolates specific additives and contaminants from the bulk polymer matrix [3]. Despite resolving physical separation challenges, the solvent-based operation encounters severe rheological and mass transfer limitations. Dissolving high-molar-mass polymers can generate highly viscous solutions, severely restricting industrial pumping and mixing operations. Additionally, the simultaneous presence of multiple additives with diverse solubility profiles complicates the solvent selection, demanding multi-stage extraction protocols [32,37,38,57,58].

Consequently, selective dissolution operates as a niche unit operation restricted to specific polymer blends.

Following the dissolution stage, recovering the targeted polymer requires controlled reprecipitation, achieved by introducing an anti-solvent or altering thermal conditions to induce phase separation. The liquid mixture subsequently requires extensive downstream separation, typically distillation, to recover both the solvent and the anti-solvent for continuous recirculation. The reliance on massive volumes of volatile and potentially toxic organic solvents imposes economic and environmental constraints. Nevertheless, when mechanical and physical fractionations fail, solvent-based dissolution provides a chemical route to separate polymers exhibiting overlapping specific masses, including heterogeneous polyolefin mixtures [3,32,37,38,57–59].

Operational and Environmental Implications of Wet Techniques

Wet separation technologies impose systemic challenges across the polymer recycling value chain. The massive water footprint imposes continuous solvent input and the implementation of rigorous wastewater treatment protocols to manage contaminated effluents containing inorganic salts, surfactants, and residual nanoparticles. Furthermore, the recovery of saturated polymer flakes dictates a mandatory downstream drying stage. This processing step significantly elevates the specific energy consumption of the facility, often representing the highest operational expense within the sorting line. The transition toward dry sorting alternatives or the integration of closed-loop water recovery systems remains a critical requirement to mitigate the environmental burden and financial intensity of density-based separation.

3.3. Additional Remarks

Industrial material recovery facilities prioritize preliminary sorting and dry separation technologies to bypass the operational bottlenecks inherent to wet processing. Implementing fluid-based separations introduces severe logistical constraints, primarily the management of massive solvent volumes, usually water, which mandates rigorous downstream effluent purification and continuous fluid recirculation. Furthermore, wet operations demand the necessary implementation of drying stages, drastically elevating the financial and environmental footprint of the recycling plant. Consequently, the commercial market predominantly supplies mature dry sorting equipment capable of routinely achieving purity rates exceeding 95% for targeted fractions.

Conversely, the industrial maturity of wet separation remains uneven. While macroscopic density tanks and mechanical jigging operate as established commercial technologies, advanced dynamic fluid separations often persist in developmental or pilot phases. Ultimately, integrating robust mechanical and physical unit operations successfully generates concentrated polymer streams from mixed municipal waste, isolating primary commodities including PE, PP, PET, PS, and PVC. Delivering standardized and uncontaminated polymer fractions resolves the fundamental feedstock bottleneck for downstream depolymerization. The capacity to engineer purified input streams directly enables the industrial implementation of advanced chemical recycling strategies.

4. Sensor-Based Sorting

Sensor-based automated sorting utilizes advanced detection mechanisms to segregate targeted polymers and contaminants from complex municipal solid waste streams. Depending on the targeted physical or chemical property, facilities implement distinct sensor arrays. Spectroscopic sensors elucidate the macromolecular composition of complex mixtures utilizing infrared, visible, and ultraviolet radiation. Furthermore, complementary

detection systems evaluate morphological and physical attributes utilizing color line scan cameras, electrical conductivity meters, and electromagnetic sensors [34].

Following signal acquisition, sorting facilities rely on advanced mathematical and statistical protocols to interpret the spectral data and actuate the mechanical ejection systems in real time. Figure 7 presents a comprehensive overview of the fundamental working principles of the primary spectroscopic techniques, highlighting the specific electromagnetic wavelength ranges (Figure 7A) [9,13,20,37,41,43,44,60]. The electromagnetic spectrum dictates the specific physical interaction between the incident radiation and the polymer matrix. Visible light sensors operate within the 400 to 700 nm range, capturing macroscopic color profiles. Near-infrared spectroscopy utilizes the 700 to 2500 nm domain, exciting molecular vibrational overtones to generate distinct polymer signatures. In contrast, mid-infrared techniques probe fundamental vibrational modes between 2500 and 25,000 nm, yielding highly specific molecular fingerprints. Raman spectroscopy operates through inelastic photon scattering to detect molecular vibrations. Moving to higher energy domains, X-ray fluorescence utilizes wavelengths below 10 nm to eject inner shell electrons, while laser-induced breakdown spectroscopy employs high-energy focused pulses to generate localized surface micro-plasmas, capturing atomic emission spectra.

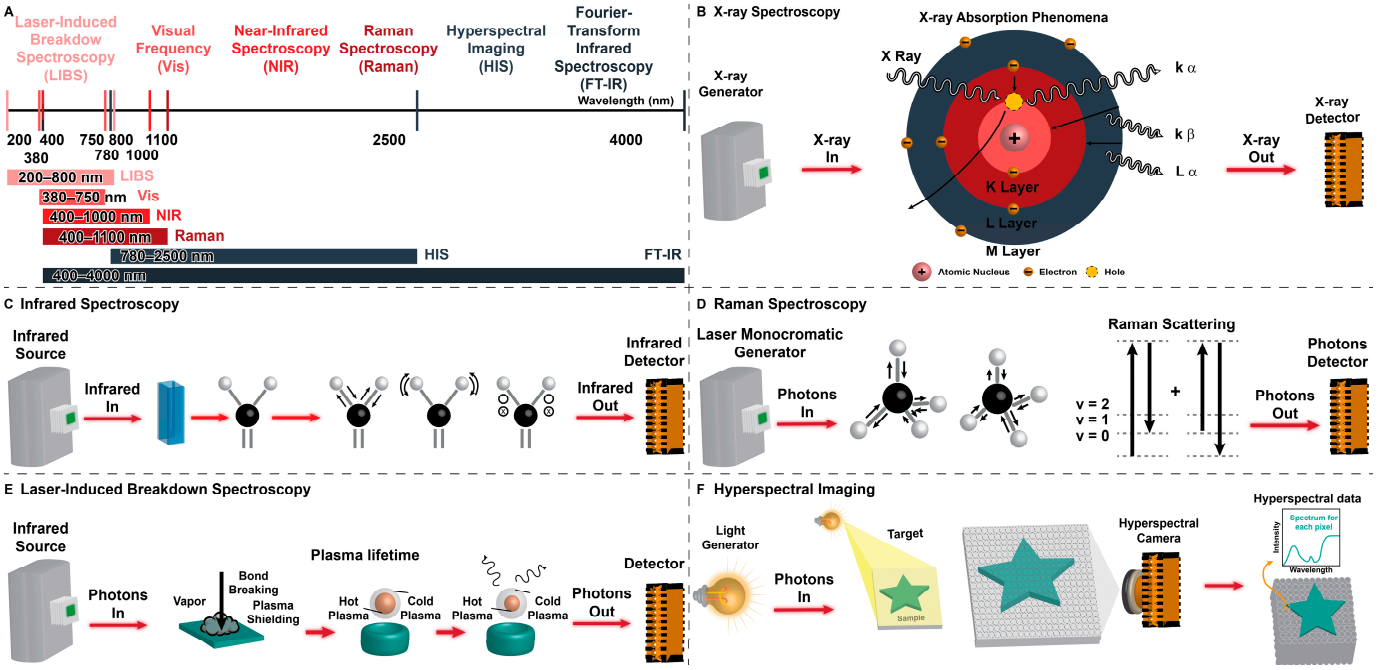


Figure 7. Main spectrometric techniques: (**A**) wavelength range and spectral distribution of the main spectrometric techniques; (**B**) X-ray spectroscopy: an incident X-ray beam excites an inner-shell electron, which is ejected; an outer-shell electron tran-sitions to the lower energy level, emitting a characteristic secondary X-ray detected by the sensor; (**C**) infrared spectroscopy: electromagnetic radiation induces molecular vibrations (stretching and bending), which are measured as absorption patterns; (**D**) Raman spectroscopy: monochromatic light interacts with molecular vibrations, resulting in inelastic scattering (Raman shift) detected as a change in photon energy; (**E**) laser-induced breakdown spectroscopy (LIBS): a high-energy laser pulse creates a micro-plasma on the material surface, and the emission spectra of the cooling plasma are analyzed; and (**F**) hyperspectral imaging: spatial and spectral data are captured simultaneously, creating a three-dimensional datacube to map the chemical composition of the surface. The arrows indicate the path of the radiation and the directional displacement of atoms during molecular vibrations. The empty circles and the circles with an 'x' represent atomic movement out of the plane and into the plane, respectively. out of the plane and into the plane, respectively.

While multiple spectroscopic methods extract characteristic spectral data to identify distinct polymer types, industrial implementation reveals severe comparative trade-offs regarding operational speed, environmental sensitivity, and detection limits (Table S3). Near-infrared spectroscopy functions as the industry standard, providing high-speed classification and high industrial maturity for transparent and brightly colored polyolefins and polyesters. However, near-infrared sensors fail to process black polymers due to the total absorption of the incident radiation by carbon black additives. To overcome the optical limitation, facilities explore X-ray fluorescence and laser-induced breakdown spectroscopy. X-ray fluorescence successfully identifies black plastics but remains restricted to detecting specific elemental markers, including chlorine in PVC. Conversely, laser-induced breakdown spectroscopy provides rapid atomic emission analysis but exhibits extreme sensitivity to surface contaminants [60]. Furthermore, molecular techniques, including Raman and Fourier transform infrared spectroscopy, offer highly specific polymer identification but suffer from severe signal degradation in the presence of surface moisture, limiting application in wet processing lines.

To address the intrinsic optical limitations of conventional passive sensors, recent patented innovations propose active identification strategies. Industrial processes utilizing fluorescent tagging or visible light-absorbing molecules applied directly to the polymer matrix automate the sorting operations. The engineered markers enable precise sorting based on customized chemical signatures, bypassing the conventional limitations of overlapping spectral responses and dark pigmentation [15,61,62].

4.1. Comparative Analysis of Optical Sensors

The selection of a sensor-based sorting architecture involves complex trade-offs between chemical specificity, acquisition speed, and environmental resilience. While near-infrared spectroscopy remains the benchmark for high-throughput polyolefin recovery due to its industrial maturity, the technology fails to address the "dark-plastic" bottleneck. Conversely, techniques such as XRF and LIBS resolve the carbon-black absorption issue but introduce constraints regarding elemental proxy reliance or extreme surface sensitivity. Table 2 summarizes the operational parameters and industrial viability of the primary spectroscopic methods analyzed in this review.

Table 2. Comparative performance of spectroscopic sensors in plastic waste sorting.

Technology	Detection Logic	Operational Speed	Dark Plastics	Surface Sensitivity	Industrial Maturity
NIR	Molecular Vibrations	Ultra-High	No	Low	Commercial Leader
XRF	Elemental Markers	High	Yes	Very Low	High (PVC/Additives)
LIBS	Atomic Emission	High	Yes	High	Emerging/Pilot
Raman	Inelastic Scattering	Low to Moderate	No	High (Fluorescence)	Low (Lab/Niche)
FTIR	Mid-IR Absorption	Moderate	No	Very High (Moisture)	Moderate (QC)

4.2. X-Ray Fluorescence (XRF)

X-ray fluorescence utilizes high-energy electromagnetic radiation, encompassing wavelengths between 0.001 and 10 nm, to determine the elemental composition of polymer flakes. Incident X-rays excite inner shell electrons of the constituent atoms, ejecting the particles from the original orbitals (Figure 7B). The resulting atomic ionization creates inner shell vacancies, forcing outer shell electrons to transition to lower energy states. The electronic

transition releases quantized energy as secondary X-ray emissions, establishing a characteristic elemental fingerprint [20,37,60].

Crucially, and unlike conventional optical sensors, X-ray fluorescence remains completely unaffected by carbon black pigmentation, enabling the reliable identification of dark and black polymers. However, the high-energy technique presents a fundamental operational limitation: the sensor cannot detect the hydrocarbon polymer backbone. Consequently, the automated system infers the polymer identity exclusively by quantifying specific elemental markers, notably detecting chlorine content to isolate poly(vinyl chloride) or identifying heavy metals to segregate plastics containing brominated flame retardants. Facilities continuously integrate the elemental detection units with high-speed mechanical ejectors to process complex waste streams. Commercial suppliers providing industrial X-ray sorting equipment include Redwave, Tomra, Pellenc ST, and Steinert [9,13,20,37,41,43,44,60].

4.3. Near-Infrared Spectroscopy (NIR)

Near-infrared spectroscopy operates through the interaction of incident electromagnetic radiation, spanning the 750 to 2500 nm domain, with the polymer matrix. The incident photons excite molecular vibrational overtones and induce modifications in the rotational modes of covalent bonds, primarily carbon–hydrogen and carbon–oxygen linkages, generating distinct spectral reflectance profiles (Figure 7C). The optical method provides instantaneous qualitative and semi-quantitative analyses, establishing near-infrared as the dominant and most commercially mature spectroscopic technology implemented in industrial material recovery facilities for polymer sorting and quality control [63].

Despite the widespread industrial consolidation, near-infrared sensors exhibit an optical vulnerability when processing dark or black polymer fractions. The incorporation of carbon black pigments into the polymer matrix causes the total broadband absorption of the incident NIR radiation [63]. Consequently, the optical sensor receives negligible backscattered reflectance, failing to detect the underlying molecular vibrations and the dark plastics. To specifically address the detection of black plastics, recent technological advancements have successfully introduced alternative spectroscopic methods, such as LIBS and Mid-Infrared (MIR) spectroscopy, which bypass the broadband absorption limitations of conventional NIR [20,37,60]. To mitigate the general optical limitations and secure high separation purity for transparent and colored fractions, facilities systematically integrate the near-infrared optical units with upstream mechanical ballistic separators and real-time pneumatic ejection modules [20,37,60].

Commercial entities supplying mature near-infrared sorting equipment include Tomra, Steinert, Pellenc ST, Sesotec, Redwave, Stadler, Amut, and Trinamix [20,30,31,37,40,64–67]. To further expand the operational capabilities, recent 2024 patent applications disclose the integration of NIR sensors with visible light spectroscopy. The multispectral approach targets complex industrial separation bottlenecks, specifically aiming to isolate food-grade plastics from highly heterogeneous post-consumer waste streams [61,62,68].

4.4. Raman Scattering Spectroscopy (RSS)

Raman spectroscopy operates through the inelastic scattering of monochromatic laser radiation, providing highly specific molecular fingerprints based on vibrational and rotational transitions (Figure 7D). Upon laser illumination, the majority of photons undergo elastic Rayleigh scattering without energy alteration. Conversely, a minute fraction of the incident photons exchanges energy with the molecular vibrations of the polymer matrix, resulting in frequency-shifted Raman scattering. The resulting spectral profile characterizes

specific functional groups, macromolecular architecture, and polymer chain orientation without requiring prior sample preparation [37,44].

Despite the theoretical capability to identify diverse macromolecular structures, the primary drawback of Raman spectroscopy for industrial sorting is its severe susceptibility to fluorescence interference. The post-consumer polymer matrix inherently contains diverse additives, colorants, surface contaminants, and degradation products that generate intense broadband fluorescence upon laser excitation. Because the quantum yield of fluorescence exponentially exceeds the inherently weak inelastic Raman scattering, the luminescent emission completely masks the characteristic vibrational peaks, effectively blinding the optical sensor [37,44].

Consequently, while the optical technique presents a distinct operational advantage of remaining unaffected by surface moisture, because water constitutes a weak Raman scatterer, the persistent fluorescence interference severely restricts the reliability of the sensor when processing highly heterogeneous and pigmented waste streams. To leverage the high chemical specificity exclusively for non-fluorescent fractions, facilities integrate the optical detection units with high-speed pneumatic ejection mechanisms, continuously fractionating the targeted polymers [37,44].

4.5. Laser-Induced Breakdown Spectroscopy (LIBS)

Laser-induced breakdown spectroscopy operates through the localized ablation of the polymer surface utilizing high-energy focused laser pulses. The intense photon delivery vaporizes and ionizes a microscopic volume of the material, generating a transient high-temperature micro-plasma (Figure 7E). As the excited atoms and ions cool and transition back to lower energy states, the particles emit specific photons across the ultraviolet and visible spectra. Optical spectrometers capture the resulting atomic emission spectra, providing precise quantification of the elemental composition without requiring prior sample preparation [13,20,37,41,43,60,69].

Crucially, because the technique relies on atomic emission rather than molecular reflectance, laser-induced breakdown spectroscopy fundamentally resolves the carbon black limitation that restricts NIR sensors. The optical mechanism successfully identifies black and heavily pigmented polymers by analyzing the fundamental carbon, hydrogen, nitrogen, and oxygen emission ratios to deduce the underlying macromolecular architecture. Furthermore, the micro plasma generation detects trace heavy metals and inorganic fillers, enabling the targeted separation of hazardous additives from the recyclable plastic stream [20,37,60].

Despite providing microsecond acquisition times and resolving the dark pigmentation bottleneck, the industrial deployment of this technology encounters severe surface sensitivity constraints. The laser ablation penetrates only a few micrometers into the polymer flake. Consequently, surface dirt, residual moisture, and organic coatings directly participate in the plasma formation, severely distorting the elemental signature of the bulk polymer. To leverage the rapid elemental analysis while mitigating false classifications, material recovery facilities must implement rigorous upstream washing and drying protocols before integrating the optical detection units with high-speed pneumatic ejection mechanisms [13,41,43].

4.6. Hyperspectral Imaging (HSI)

Hyperspectral imaging integrates spatial optical detection with continuous spectroscopic analysis, generating a multidimensional data array. Rather than capturing simple macroscopic color, the advanced sensor acquires a complete reflectance or emission spectrum for every discrete spatial pixel across contiguous electromagnetic bands (Figure 7F).

The simultaneous acquisition of spatial and chemical data enables the precise morphological and macromolecular mapping of highly heterogeneous waste streams [30,37,60].

In industrial material recovery facilities, hyperspectral sensors function as critical quality control mechanisms to continuously monitor and validate polyolefin sorting lines. By coupling high-resolution spatial imaging with NIR or visible spectroscopy, the automated systems detect microcontaminants, identify multilayer packaging, and segregate distinct polymer grades exhibiting identical macroscopic geometries.

Despite the unprecedented classification accuracy, generating and analyzing massive multidimensional data structures imposes severe computational bottlenecks. Real-time industrial sorting demands ultra-high-speed data processing architectures and advanced machine learning algorithms to interpret the spectral pixels and actuate the pneumatic ejection valves without reducing the continuous conveyor belt velocity. To maximize throughput and separation purity, facilities systematically integrate the hyperspectral detection modules directly above continuous flow mechanical separators, ensuring immediate physical removal of the targeted polymers [20,30,37,41,60,65,66].

4.7. Fourier-Transform Infrared Spectroscopy (FTIR)

Fourier-transform infrared spectroscopy operates within the mid-infrared electromagnetic domain, typically spanning wavelengths between 2500 and 25,000 nm. The analytical technique relies on the absorption of infrared radiation by specific molecular functional groups, generating highly resolved vibrational and rotational spectra. Unlike conventional dispersive spectrometers that sequentially isolate wavelengths utilizing mechanical monochromators, the advanced optical system employs an interferometer to simultaneously modulate and capture the entire infrared spectrum. The acquired interferogram undergoes a mathematical transformation to yield a highly specific molecular fingerprint, enabling the precise structural identification of complex polymer architectures, including polyethylene terephthalate, polyvinyl chloride, and polystyrene [41,70].

Despite providing superior chemical specificity compared to standard near-infrared sensors, the industrial deployment of Fourier-transform infrared spectroscopy encounters fundamental physical limitations. Mid-infrared radiation exhibits significantly reduced optical penetration depth into the polymer matrix. Furthermore, the molecular vibrational modes render the optical sensor extremely sensitive to surface moisture. Because water molecules strongly absorb infrared radiation within the targeted operational bands, microscopic residual humidity on the plastic flake severely distorts the resulting spectral signature. Consequently, to leverage the high-resolution detection capabilities, material recovery facilities must implement rigorous thermal drying unit operations before integrating the spectroscopic modules into continuous sorting lines.

5. Chemometric Techniques for Data Analysis

Chemometrics constitutes a specialized discipline that employs advanced mathematical and statistical protocols to extract actionable intelligence from complex chemical data. Within automated material recovery facilities, the computational approach bridges the critical gap between raw spectroscopic acquisition and real-time mechanical actuation. By systematically applying exploratory data visualization and confirmatory model validation, chemometric protocols translate massive optical data streams into precise polymer classifications. While traditionally consolidated in pharmaceutical quality control, robust mathematical modeling currently drives the technological advancement of intelligent plastic solid waste sorting [30,31,37,64,70–72].

The computational toolset encompasses a broad spectrum of algorithms, ranging from classical multivariate statistics, including Principal Component Analysis, Linear Discrim-

inant Analysis, and Partial Least Squares, to advanced machine learning architectures, notably k-Nearest Neighbors, Support Vector Machines, Random Forests, Artificial Neural Networks, and Convolutional Neural Networks [73]. Crucially, industrial implementation dictates a severe operational trade-off between classification accuracy and real-time processing speed for real-time plastic identification. Classical linear models, such as Partial Least Squares Discriminant Analysis (PLS-DA) and Linear Discriminant Analysis (LDA), offer fast processing speeds (often requiring under 1 millisecond per spectrum) and low hardware requirements [64,74]. However, these algorithms typically exhibit lower classification accuracies (ranging from 80% to 90%) when processing highly overlapped spectra and frequently fail to resolve severe nonlinear spectral distortions caused by surface moisture, polymer degradation, and complex additive profiles [64,75].

Conversely, non-linear machine learning algorithms and deep learning architectures, particularly Support Vector Machines and Convolutional Neural Networks, demand graphical processing power to prevent latency in the pneumatic ejection systems. Despite the higher computational cost, these advanced models successfully achieve classification accuracies exceeding 95% to 98% within milliseconds [74,75]. In addition, advanced neural networks can autonomously extract hierarchical spectral features, demonstrating unprecedented robustness against surface contamination and heterogeneous flake geometries.

5.1. Principal Component Analysis (PCA)

Principal Component Analysis (PCA) operates as a fundamental multivariate statistical protocol designed to mitigate the dimensionality of massive datasets while strictly preserving intrinsic data variance. The mathematical algorithm transforms highly correlated measured variables into a reduced set of orthogonal and uncorrelated vectors, formally defined as principal components. By calculating the eigenvectors and eigenvalues derived from the data covariance matrix, the technique identifies specific multidimensional directions that maximize dataset variances. The primary eigenvector, associated with the largest eigenvalue, captures the absolute maximum proportion of the total variance, while subsequent orthogonal components systematically map the remaining decreasing variability [64].

Consequently, the linear transformation condenses essential structural information into a highly efficient matrix, isolating the most influential data features while filtering out instrumental noise and redundant background signals [64]. Within automated material recovery facilities, dimensionality reduction proves mathematically critical for high-speed optical sorting. The algorithm compresses complex spectroscopic arrays, often containing thousands of discrete points at distinct wavelengths, into a simplified coordinate space. The mathematical compression directly translates massive raw optical streams into distinct polymer classifications, enabling the central processing unit to actuate mechanical ejection valves in real time without exceeding computational limits.

5.2. Cluster Analysis

Cluster analysis functions as an unsupervised machine learning protocol designed to autonomously identify intrinsic structural patterns within unclassified data streams. By deploying specific mathematical distance metrics, the algorithm partitions complex multidimensional datasets into distinct, cohesive subgroups exhibiting high internal homogeneity. Within automated material recovery facilities, the computational technique continuously segregates incoming polymer flakes based on heterogeneous physical and chemical arrays, including macroscopic color profiles, morphological density, and predominantly, high-resolution spectroscopic signatures [76,77].

Rather than relying on simple linear thresholds, the clustering algorithm calculates the multidimensional spatial proximity between real-time sensor acquisitions and established reference libraries to rapidly classify unknown plastic fractions. The instantaneous mathematical categorization translates complex raw measurements into actionable discrete commands, directly actuating the downstream mechanical sorting architecture to ensure precise physical segregation of targeted polymer commodities.

5.3. Factor Analysis

Factor analysis constitutes an advanced multivariate statistical framework engineered to identify latent variables that drive the observed covariance within multidimensional datasets. While mathematically related to Principal Component Analysis, the algorithmic approach diverges significantly in its primary optimization objective. Rather than strictly maximizing total dataset variability through orthogonal vectors, factor analysis isolates underlying latent structures by maximizing the correlation among specific variable subsets. Furthermore, the statistical protocol accommodates nonlinear mathematical transformations, enabling a highly flexible representation of complex spectral interactions that govern heterogeneous material characteristics [78].

Within industrial plastic sorting applications, factor analysis executes dimensionality reduction. By applying mathematical transformations, the algorithm converts spectroscopic arrays into composition profiles driven by latent components. Mathematical isolation allows the automated control system to detect spectral variations associated with polymer blends, additive concentrations, or polymer degradation states. Consequently, the computational protocol translates optical data into discrete real-time actuation commands, guiding downstream mechanical ejection units to execute separation decisions.

5.4. Discriminant Analysis

Discriminant analysis operates as a statistical technique utilized to categorize observations into distinct groups based on a set of predictor variables (for example, spectral data of specific polymer samples). The mathematical protocol provides valuable insights into the pivotal variables contributing significantly to group separation, identifying the most critical variables to distinguish between groups (for example, specific combinations of spectral signals at defined wavelengths). The methodology enhances the understanding of complex datasets and facilitates the accurate identification of polymers within automated sorting lines [65].

5.5. Regression Analysis

Regression analysis formulates mathematical models to quantify relationships among variables. By minimizing the residual error between a defined predictive equation and acquired data, the statistical protocol predicts target outputs based on independent sensor inputs. Within material recovery facilities, regression algorithms can correlate equipment operational parameters and outputs with polymer material characteristics [64]. Therefore, the mathematical procedure can convert acquired spectral arrays into continuous composition profiles. The central processing unit translates regression outputs into actuation commands, directing downstream mechanical ejection mechanisms to execute polymer separation.

5.6. Partial Least Squares (PLS) Regression

Partial Least Squares (PLS) regression formulates covariance models between predictor matrices and response matrices. By projecting predictor variables and response variables into a latent space, the algorithm extracts components that maximize the covariance between datasets. The mathematical protocol processes spectral arrays to predict polymer

stream compositions. Within material recovery facilities, the regression model can correlate material characteristics directly with polymer yields. The central processing unit translates predictions into mechanical actuation commands, guiding pneumatic valves to execute polymer separation [79].

5.7. ANOVA (Analysis of Variance)

Analysis of variance (ANOVA) partitions total observed variability into components attributable to specific sources, evaluating the probability that differences between dataset means result from controlled process variables. The statistical framework calculates the variance ratio to determine the impact of manipulated operational parameters on polymer recovery metrics. Within automated material recovery facilities, the methodology compares performance indicators across distinct equipment configurations and sensor settings [80]. The analytical protocol identifies if adjustments in conveyor belt velocity or pneumatic pressure alter the final polymer purity, for instance. In addition, the mathematical procedure can be used to validate experimental designs and monitor longitudinal process stability. Unlike classification algorithms, analysis of variance executes hypothesis testing on population parameters rather than assigning individual polymer flakes to chemical categories based on spectral characteristics.

5.8. Future Trends in Chemometric Integration

The integration of multivariate algorithms and high-speed spectroscopic sensors establishes the computational foundation for the digital transformation of material recovery facilities. Beyond basic classification, advanced chemometric protocols enable the generation of digital fingerprints for recovered polymer fractions, ensuring the chemical traceability required for high-grade circular economy applications. Data fusion strategies, combining inputs from hyperspectral imaging and X-ray detectors, can mitigate traditional limitations associated with surface contamination and dark pigmentation. Consequently, robust mathematical frameworks can provide the standardized feedstock homogeneity required by downstream chemical recycling processes, where precise control over additive concentrations and polymer purity dictates the final yield of upcycled monomers.

6. Layouts of Sorting Plants and Interactions Among Sorting Techniques

Urban solid waste separation plants process post-consumption plastic residuals to prevent recyclable waste materials from entering landfills or the environment, mitigating land and groundwater pollution. In sorting facilities, the correct sequence of separation equipment dictates the recovery rate of recyclable and organic materials. Identifying the composition of the received solid waste and defining the target fractions enables the selection of specific sorting techniques and equipment. The available techniques present diverse operational parameters, increasing the complexity of technology selection [73].

In an integrated sorting line, distinct separation technologies function synergistically to overcome individual operational limitations. Mechanical conditioning equipment, including trommel screens and ballistic separators, can execute the critical preliminary stage by fractionating the heterogeneous waste stream based on specific mass and 2D/3D geometry. The physical segregation prevents material overlap and prepares the uniform monolayer flow required by downstream optical sensors. Subsequently, magnetic and eddy current separators extract ferrous and nonferrous metals, protecting delicate shredding units from mechanical failure and ensuring polymer purity. Following physical preparation, high-throughput spectroscopic sensors, primarily NIR units, execute bulk polymer classification. To resolve specific optical bottlenecks, facilities integrate complementary detection mechanisms, coupling NIR with XRF or LIBS to recover black plastics and identify trace

additives. The integrated architecture ensures that upstream physical sorting maximizes the optical efficiency of downstream chemical detectors.

No single method processes all plastic waste fractions. Jolivet et al. analyzed the combined application of LIBS and Raman scattering spectroscopy (RSS), noting the combination shares instrumentation since both methods utilize laser beams with distinct energy requirements [81]. Shameem et al. evaluated a hybrid LIBS-RSS system to sort PE, PP, PET, and PS, yielding complementary spectral data [7]. RSS separates transparent polymers, but classification accuracy declines when processing colored plastics [82]. Conversely, LIBS separates the analyzed plastic streams regardless of color when the algorithm employs cluster analyses, whereas separation accuracy decreases when the model applies Principal Component Analysis (PCA) for dimensionality reduction of spectral data [83]. NIR data models yield low classification accuracy independently, while MIR models achieve classification metrics that are similar to the ones achieved with the combined NIR-MIR model, indicating NIR data redundancy in specific hybrid systems [84].

Based on technoeconomic frameworks established by Cimpan et al. [85], sorting plants fall into four operational categories defined strictly by processing capacity, mechanical complexity, and the integration level of automated optical sensors. Basic plants operate at low capacity, execute fundamental material conditioning steps, including sieving and air classification, and rely entirely on manual sorting. Medium plants operate at intermediate capacity and execute multiple conditioning steps, including ballistic separation, utilizing automatic and manual sorting, usually combined with manual quality control. Medium-plus plants process volumes that are similar to volumes processed by medium plants, although executing diverse plastic sorting tasks and running the facility in three shifts to increase the total processing capacity [86]. Advanced plants process high volumes through fully automated sensor-based sorting techniques and employ integrated quality control protocols, achieving the highest throughput and purity values required for modern municipal solid waste processing.

Input stream types and waste quality define sorting plant implementation and specific equipment selection. Input streams fall into four categories: (i) single stream, mixing all recyclables; (ii) mixed municipal waste stream, consisting of non-hazardous waste collected from distinct facilities; (iii) dual stream, separating inputs into separate bins; and (iv) pre-sorted stream, containing recyclables sorted by materials recovery facilities (MRFs) before reaching the recycling plant [86]. Materials recovery facilities substitute wet processing with dry processing to eliminate energy, environmental, and financial costs associated with solvent use. To execute dry processing, facilities implement rotating screens, ballistic separators, and sensor-based optical sorting.

6.1. Players of Sorting Plants

The sorting technology sector comprises waste management operators and specialized equipment manufacturers whose proprietary innovations directly dictate facility layout and operational efficiency. Environmental service providers, such as Republic Services (USA) and Suez/Veolia (Europe), execute logistics and plant operations, while engineering firms supply the technological infrastructure, customizing hardware solutions based on regional waste composition.

Specific manufacturers dictate equipment availability and physical plant design through specialized mechanical and optical integrations. Stadler (Germany) engineers turnkey plants relying on proprietary ballistic separators that physically prepare the material flow, optimizing the spatial footprint of the preliminary mechanical stage. Steinert (Germany) produces magnetic and eddy current separators, integrating sensor-based sorting equipment to recover metal and plastic fractions simultaneously, reducing the necessity

for extensive sequential conveyor lines. Pellenc ST (France) and Redwave (Austria) develop optical sorting instrumentation adapted for high-throughput industrial environments.

The Tomra Group (Norway) supplies multi-sensor classification systems operating with near-infrared, visible-light, and laser-induced scanning. The integration of multiple optical detectors within a single unit enables compact plant designs that resolve diverse optical blind spots during a single sorting stage. Additional manufacturers include Amut (Italy), producing washing lines, alongside Bianna (UK/Spain) and Bub-Anlagenbau (Germany). Material recovery facilities integrating equipment from the listed manufacturers process multi-component waste inputs. Automated facilities segregate over 16 distinct material fractions, including specific polymer grades (transparent, blue, and green PET; HDPE; PP; PS; and flexible films), generating the high-purity recovery streams required to sustain circular economy protocols [87,88].

6.2. Examples of Sorting Plants

The targeted final product dictates the sorting plant layout. The presence of pre-sorted input streams alters the facility configuration. Sorting plants processing urban solid waste integrate sequential separation systems designed for polymer recovery, targeting subsequent recycling protocols and the production of refuse-derived fuels [89].

Figure 8 illustrates the schematic representation of a baseline sorting facility. The reception area receives collection vehicles and compacted waste volumes. Municipal solid waste bags enter bag opening equipment, tearing the polymer matrix to release raw waste onto a primary separation conveyor. The waste stream traverses a manual quality control section to extract process-disrupting materials, preventing mechanical failure and minimizing maintenance downtime [90]. Ferrous magnetic materials undergo extraction via magnetic overhead belts or head pulleys. A trommel screen processes the flowing waste stream to extract glass and organic residues. The trommel divides materials into two primary streams: oversized fractions continue along the main sorting line, whereas undersized fractions fall through the screen. Secondary sieving processes separate retained undersized fractions, isolating glass pieces for recycling [91–93] and routing organic matter to composting facilities [19,94]. Following rotary screening, vibrating conveyors fractionate the material into two-dimensional streams alongside three-dimensional streams containing rigid plastic packaging. An eddy current separator processes the remaining flow to extract nonferrous metals. The residual waste stream contains target plastic materials, which undergo final classification based on polymer type.

Tomra operational protocols specify the allocation of one to four manual quality inspectors based on the target material fraction. Guidelines recommend positioning inspectors to monitor the 2D material fraction, extracting misplaced 3D materials downstream of the ballistic separator and upstream of optical sorting units. Following multi-stage sorting, the residual fraction of 60 to 80 mm black plastic pieces constitutes less than 10 to 15% of the total input volume. The sequential sorting configuration yields raw materials suitable for waste-derived fuel production, maintaining low polyvinyl chloride (PVC) concentrations [43].

Integrating ballistic separators with sensor-based spectroscopy equipment provides rapid and precise polymer detection, increasing the final classification purity of the plant [9,13]. The coupled instrumentation executes color-based separation of plastic streams [76,95]. Following the segregation of each process fraction, the facility implements quality control protocols through manual inspection or automated optical assessment [96,97].

The Stadler Company engineers, manufactures, and assembles automated sorting systems. The manufacturer reports the implementation of over 500 municipal solid waste

sorting plants, presenting processing capacities ranging from 40,000 tons per year to 1,000,000 tons per year [89]. Facilities utilize equipment arrays matching previously described sequential models. Screening processes fractionate initial material streams based on physical dimensions and aerodynamic behavior. Wind shifting equipment extracts large area flexible films, reducing material overlap and optimizing subsequent NIR sorting stages. Magnetic and eddy current separators extract ferrous and nonferrous fractions. Manual quality control personnel verify separated polymer streams before conveyors route materials to baling presses [89]. The Ecopark 4 facility in Barcelona exemplifies a large-scale plant engineered by the company. The installation occupies 52,000 m^2 and processes 365,000 tons of municipal solid waste annually. The infrastructure required an initial investment of 52 million EUR.

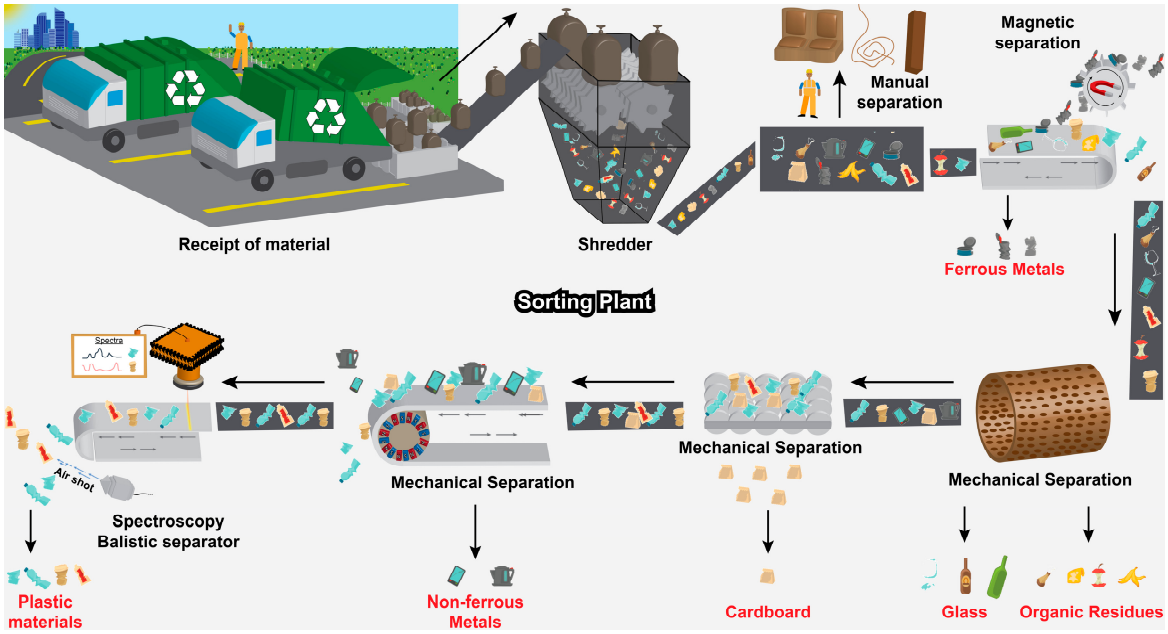


Figure 8. Schematic illustration of a generic hybrid sorting plant featuring the sequential integration of mechanical separation, sensor-based sorting, and intelligent systems. The layout shows the material flow from receipt and shredding through various separation stages: magnetic (ferrous metals), mechanical (cardboard, glass, organic residues), and spectroscopic (plastic and non-ferrous materials). The detector displays illustrative spectra from the sensor-based detection system, and the arrows at the final stage represent the directional air jets used to deflect materials into high-purity streams.

In Brazil, the Ecopark Pernambuco processes municipal solid waste using sensor-based sorting systems. The industrial plant receives approximately 250,000 tons of waste annually, recovering over 12,500 tons of recyclable materials. The facility integrates Tomra equipment and operates a dedicated plastic recovery line, classifying HDPE, PP, PET, and LDPE films. The dedicated line yields specific polymer fractions meeting purity requirements for industrial applications [98].

The Ecopark Pernambuco main feed stream handles 35 tons of raw urban waste per hour. The operational sequence initiates with mechanical bag opening, proceeding to sieving and manual sorting stages [98]. Conveyor belts route the remaining material stream to the ballistic separator, coupled with a near-infrared sensor. Figure 9 illustrates the three primary material streams classified by the ballistic air separation unit. The ballistic system isolates distinct polymer types, segregating 2D flexible materials from 3D rolling objects through the integrated operation of near-infrared spectrometers [99].

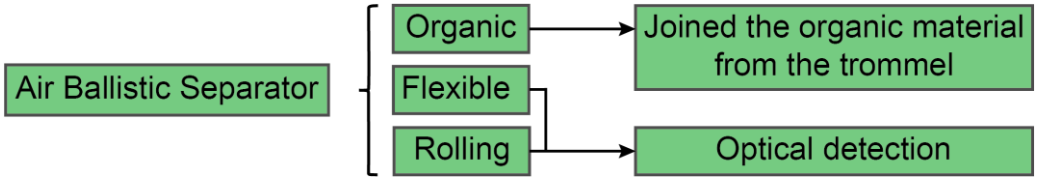


Figure 9. Illustration of the three primary material streams separated by the ballistic air separator at the Ecopark Pernambuco facility.

The increasing integration of sensor-based sorting algorithms establishes the development trajectory for future recycling infrastructure. Transitioning from manual-dependent facilities to fully automated architectures demands higher initial capital expenditures. However, automated infrastructure reduces long-term operational expenses by minimizing manual labor requirements and maximizing final output purity. The technological transition enables future facilities to adapt dynamically to changing multi-component waste streams, ensuring compliance with the strict high-purity mandates required by modern circular economy legislations [86].

6.3. A Possible Sorting Plant

The integration of reviewed separation techniques establishes a baseline design for a municipal solid waste sorting plant. Figure 10 illustrates the proposed process flowchart. Alphanumeric codes (L1 to L19) identify sequential process streams. Collection vehicles discharge waste bags into a primary reception area (L1). Shredding equipment tears polymer bags to expose raw waste onto a conveyor belt, while an integrated magnetic separator extracts ferromagnetic metals (L2), routing the residual flow to a subsequent conveyor (L3). The material flow traverses an eddy current separator to extract nonferrous metals (L4), routing residual solid waste to a subsequent conveyor (L5). To align with standard industrial practices and prevent cross-contamination, a rolling vibratory table immediately extracts cardboard structures (L6), and the remaining flow (L7) enters an upper flow air table that separates paper fractions (L8). Following the early removal of fibrous materials, the resulting stream (L9) enters a trommel screen featuring a 90 mm mesh diameter, separating the undersized fraction containing glass and organic matter (L10) from oversized recyclable materials (L11).

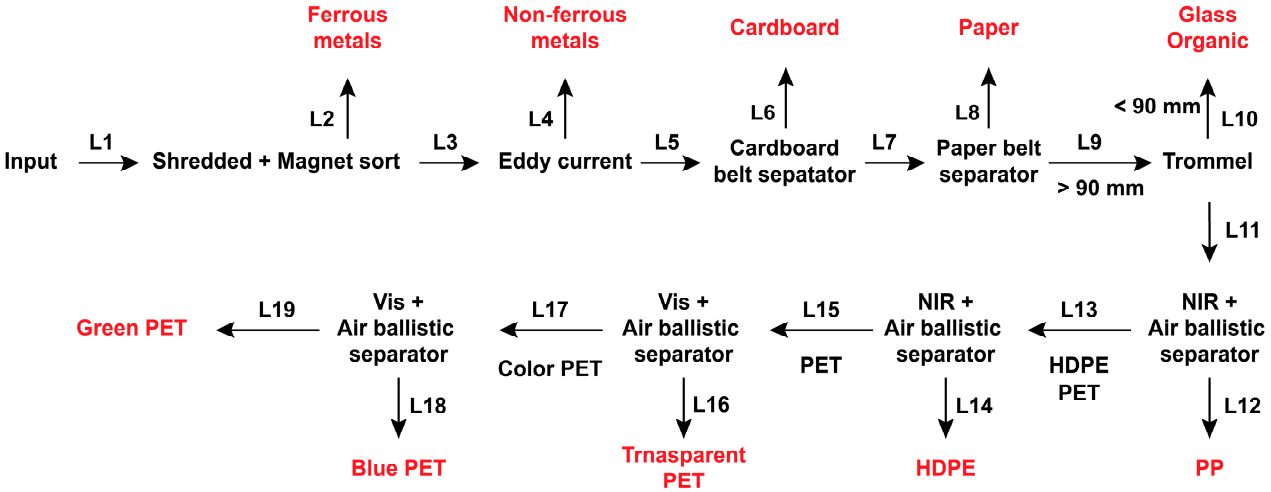


Figure 10. Proposed flowsheet for a municipal solid waste sorting plant, illustrating the sequential unit operations required to recover metals, organics, paper, and high-purity polymer fractions, including color-sorted PET.

The resulting stream (L11) contains the mixed plastic fraction. A NIR spectroscopy detector coupled with a ballistic separator can analyze stream L11 to extract polypropylene (L12) from the high-density polyethylene and polyethylene terephthalate mixture (L13). A secondary near-infrared ballistic air separator extracts high-density polyethylene (L14) from the polyethylene terephthalate stream (L15). A visible-light (VIS) spectroscopy detector integrated with a final ballistic air separator executes color-based classification of polyethylene terephthalate materials, generating isolated streams of transparent (L16), mixed color (L17), blue (L18), and green (L19) polymers. While conventional high-throughput sorting plants typically segregate PET into only two primary streams (transparent and mixed color) to prevent operational bottlenecks, the proposed flowchart represents an advanced facility equipped with multi-stage visible-light sensors capable of isolating specific pigmented fractions. The proposed advanced configuration yields ten primary product streams.

The theoretical recovery efficiency of the proposed configuration fluctuates during actual industrial operations based on input stream variables. Inherent material humidity, surface contamination, and organic matter adhesion alter the aerodynamic and spectroscopic profile of target polymers [100]. Mitigating physical variables requires dynamic calibration of unit operations and the implementation of upstream mechanical conditioning steps to guarantee baseline purity metrics. Furthermore, the anticipated production of the plant layout faces severe throughput limitations and physical bottlenecks. The primary constraint occurs during the singulation phase; as conveyor belt velocities exceed 3 m per second to maximize production rates, polymer flakes frequently overlap, blinding optical sensors and leading to the coejection of contaminants. Additionally, a critical throughput mismatch often exists between bulk physical separators and downstream high-resolution optical scanners. Finally, the mechanical latency of pneumatic ejection valves remains a decisive bottleneck, limiting the maximum number of items that can be accurately sorted per second, regardless of the optical sensor's computational speed.

6.4. Economic and Environmental Aspects

Plastic sorting operations integrate technical parameters with economic metrics and environmental impact data. Financial metrics dictate the operational viability of material recovery facilities. Operational expenses associated with municipal solid waste treatment drive the implementation of sorting infrastructure [101,102]. Material recovery facilities reduce the total waste volume requiring disposal, lowering landfill taxation while generating revenue yielding polymer streams to sustain circular economy protocols [103]. Global municipal solid waste generation reaches approximately 2.0 billion tons annually, with 33% of the total mass bypassing formal management infrastructure. Daily per capita waste generation averages 0.74 kg globally [104]. Implementing formal waste management infrastructure increases the recovery rate of recyclable polymers and routes organic fractions to composters, minimizing landfill allocation requirements.

Economic demographic classifications categorize regions into high-income, upper-middle-income, lower-middle-income, and low-income brackets. The municipal solid waste collection rate and material composition correlate directly with defined income brackets. High-income regions execute waste collection protocols reaching 96% coverage, whereas collection metrics decline to 82%, 51%, and 39% across subsequent lower-income classifications [105]. Uncollected waste primarily enters open dumpsites. Table 3 details the global waste composition, establishing that organic materials constitute 44% of the total urban solid waste mass. Regions with elevated organic fractions require robust upstream mechanical screening to protect downstream optical sensors. Conversely, high-income countries present lower organic fractions and higher recyclable material concentrations, reflecting the execution of specific circular economy public policies [106]. Effective measures

include extended producer responsibility frameworks, which mandate that manufacturers finance the end-of-life sorting infrastructure for their packaging, funding advanced optical sorting technologies. which drive financial investments into advanced sorting infrastructure, and mandatory source separation policies coupled with progressive landfill taxation, which strongly incentivize households to divert recyclables from mixed waste. By improving the purity of the collected input streams, these policies directly enhance the overall operational efficiency of material recovery facilities.

Table 3. Percentage composition of municipal solid waste categorized by global averages, national income classifications, and a specific regional case study (Al-Karak, Jordan [107]).

Local/Composition	Global Waste Composition	High-Income Countries	Upper-Middle-Income Countries	Lower-Middle-Income Countries	Lower-Income Countries	Al-Karak—Jordan
Reference	[105]	[108] ([19])	[108]	[108]	[108] ([19])	[107]
Organic material	44	32 (27)	54	53	56 (64)	28
Paper and Cardboard	17	25 (30)	12	12.5	7 (6)	44
Metals	4	6 (7)	2	2	2 (3)	4
Plastics	12	13 (11)	11	11	6.4 (9)	15
Glass	5	5 (7)	4	3	1 (3)	-
Other waste	18	19 (18)	17	18.5	27.6 (15)	9

Al-Athamin et al. evaluated the operational and financial metrics of the Al-Karak solid waste sorting plant in Jordan, computing the revenue generation required to offset facility operational expenses [107]. The methodology quantified and characterized the input stream to define target sorting fractions, evaluating distinct equipment arrays. An economic model calculated the financial viability of sorting facility configurations using three specific indicators: net present value (NPV), return on investment (ROI), and the amortization payback period [25]. The Al-Karak municipal solid waste composition comprised paper and cardboard (41%), organic material (28%), and plastics (15%). Processing the input stream generates 12,000 tons per year of recyclable materials, representing 63% of the total mass feed. The modeled sorting operation achieved an amortization period under five years by utilizing a hardware configuration containing a baling press, a primary conveyor belt, a polymer shredder, a forklift, and two collection vehicles [107].

Gadaleta et al. applied a technoeconomic model to quantify performance metrics of a material recovery facility processing plastic waste [25]. The Molfetta facility in southern Italy processes an inlet plastic feed of 19,000 tons per year. The methodology analyzed the mass and composition of input streams, computed the purity and recovery indices of recyclable fractions, established individual mass balances, and executed the financial assessment of unit operations. Executing polymer and color recognition sorting separates the input plastic stream into primary product flows and secondary by-product flows. Primary product flows undergo mechanical recycling to generate secondary raw materials, whereas the facility routes by-product flows to energy recovery incinerators [25]. Substituting fossil fuels with polymer by-product flows for energy generation reduces baseline carbon emissions, but routing by-product flows back into mechanical recycling protocols yields higher material retention within circular economy frameworks.

Contaminant polymers misallocated into secondary streams escape the recovery process, constituting the defined "lost" fraction. The facility records average mass loss values of 18.0% for PET, 3.2% for PE, 2.6% for PP, and 69.6% for flexible packaging films smaller than an A3 format. The high loss rate of flexible films dictates the mass balance between primary product flows and by-product flows, equating to 8686 tons and 9708 tons annually, respectively. Facility expenditures primarily consist of equipment amortization install-

ments, mechanical maintenance, personnel payroll, and variable energy costs, representing 90% of the total annual operational budget. The Molfetta material recovery facility yields an annual net revenue of 234,636 EUR per year, establishing a specific profit margin of 12.58 EUR per ton of sorted waste [25].

Medina-Mijangos et al. executed a technoeconomic analysis of a light packaging and bulky waste sorting facility in Gavà-Viladecans, Spain [109]. The applied methodology utilized a social cost–benefit model, computing direct operational impacts and environmental externalities to determine the net financial benefit, validating the economic profitability of unit operations. The infrastructure integrates a light packaging treatment unit and a bulky waste processing unit. The facility processed 22,806 tons of light packaging waste and 63,275 tons of bulky waste during the 2017 operational cycle. Dividing total annual expenditures by the consolidated processed mass (86,081 tons) establishes a specific operational cost of 96.2 EUR per ton [109].

The facility revenue stream derives from material reuse, mechanical recycling, and energy recovery protocols. Financial returns originate from commercializing treated light packaging waste, directing 15,868 tons of sorted polymers to secondary mechanical recycling plants and routing 6938 tons of residual materials to energy recovery incinerators. Municipal waste management service fees generate the primary financial intake, accounting for 49.89% of the revenue from light packaging processing and 38.83% from bulky waste operations. Life cycle assessment (LCA) algorithms compute that facility operations prevent the atmospheric emission of 69,655 tons of CO_2 equivalents per year [109].

Cimpan et al. mapped operational parameters of material recovery facilities across North America, the United Kingdom, Germany, the Netherlands, and adjacent European nations, analyzing specific processing metrics [110]. Automated sorting facilities execute mechanical recirculation of residue streams, coupling feedback loops with automated quality control to increase the final polymer recovery index and reduce the ultimate discard volume [110]. The multi-stage recirculation protocol concentrates target polymers and isolates contaminant fractions, decreasing total material loss. Elevated purity and volume of the final output generate higher market revenues, although the final non-recoverable sorting residue still accounts for approximately 20% of the initial input mass [110].

Utilizing operational data from three Dutch plastic packaging recovery plants, the study established an empirical algorithm to compute recovery efficiency across distinct operational scenarios. The total operational expenditure for processing recycled plastic packaging waste ranges from 660 EUR to 870 EUR per ton when integrating preliminary isolation protocols. Facilities relying entirely on downstream post-separation face increased processing costs, requiring expenditures between 870 EUR and 920 EUR per ton of recovered material [110].

The mass of recyclable materials extracted by mechanical biological treatment facilities fluctuates according to the specific composition of the residual municipal solid waste feed, presenting variations driven by seasonal conditions. The overall recovery rates respond to the initial waste input profile, the specific hardware configuration, and the targeted output fractions. The total operational expenditure for processing recycled plastic packaging waste ranges from 660 EUR to 870 EUR per ton when integrating municipal source separation. Facilities relying entirely on post-separation protocols face increased processing costs, requiring expenditures between 870 EUR and 920 EUR per ton of recovered material [110].

Despite the provided economic assessments, current technoeconomic models lack standardized evaluation metrics, presenting high dependency on regional waste compositions, localized energy costs, and specific municipal subsidies. Furthermore, previous studies frequently restrict the recovery index analysis to a limited number of target products, masking actual operational costs associated with contaminant streams and secondary

waste disposal [111]. Consolidating the operational data from Jordan, Italy, Spain, and Northern Europe demonstrates a consistent industrial trend: initial capital expenditures for automated sensor-based sorting are rapidly offset by increased output purity, reduced landfill taxation, and enhanced LCA metrics [86,100]. Closing existing methodological gaps requires future research to integrate dynamic life-cycle assessment algorithms with real-time automated sorting data, establishing standardized financial evaluation frameworks applicable across distinct global economic regions.

7. Challenges and Future Prospects

The current body of literature examines individual unit operations under controlled laboratory conditions, omitting the operational complexities of multi-stage industrial sorting. Existing reviews center on chemical identification via near-infrared spectroscopy for standard polymers, while neglecting the impact of surface contamination, multilayer structures, and black plastics on real-time throughput. The absence of standardized techno-economic metrics across previous studies precludes the comparative assessment of different sorting configurations. The transition from laboratory-scale accuracy to industrial-scale viability demands the integration of comprehensive data on material flows and specific energy consumption of high-capacity separators.

The integration of multi-sensor arrays addresses inherent limitations of single-wavelength detection. Combining near-infrared spectroscopy with X-ray fluorescence and color sensors facilitates the identification of multi-layer materials and complex polymer blends. Data fusion algorithms synchronize heterogeneous signals to increase classification accuracy within high-speed conveyance systems. The methodology enables the detection of additives and flame retardants that bypass traditional optical separators, ensuring the production of high-purity feedstock for chemical recycling processes.

The evolution of machine learning architectures, particularly deep convolutional neural networks, establishes the capacity to process hyperspectral data streams and resolve identification bottlenecks associated with multi-layer packaging and heterogeneous waste streams. Computational processing resolves spectral overlaps caused by thermal degradation and surface residues, while autonomous feature extraction eliminates the requirement for constant manual calibration to maintain separation stability. The employment of edge computing units minimizes latency in real-time actuation, allowing mechanical ejectors to target specific polymer fractions within milliseconds. Future prospects comprise process hybridization, where sensor data fusion retrofits existing analog lines to maximize resource recovery through automated vision bridges and robotic sorters targeting flexible films and small format plastics escaping mechanical separation. Scaling sorting technologies necessitates the formulation of public–private co-investment models to mitigate capital intensity and bridge the gap between recycling rates and circular economy targets.

The modernization of existing material recovery facilities necessitates the implementation of modular sorting units. Retrofitting analog processing lines with intelligent vision systems and robotic sorting arms maximizes resource recovery without requiring complete infrastructure replacement. Technological hybridization supports the transition toward circular economy models by increasing the volume of plastics diverted from landfills. Establishing feedback loops between sorting outcomes and upstream polymer design facilitates operational sustainability within the plastic value chain.

8. Conclusions

The consolidation of bibliometric data and patent analyses reveals a critical divergence between academic research and industrial deployment within plastic waste sorting. While the scientific literature predominantly investigates fundamental spectroscopic accuracy

under controlled conditions, recent patent disclosures indicate a definitive industrial shift toward multi-sensor data fusion, edge computing, and real-time pneumatic actuation to resolve physical bottlenecks, notably surface moisture and black plastics. Consequently, achieving the high-purity material streams required for circular economy applications dictates a mandatory technological transition from strictly mechanical processing to automated sensor-based architectures. Current industrial layouts establish that coupling near-infrared (NIR) and visible-light (VIS) spectroscopy with ballistic air separation units constitutes the modern standard for material recovery facilities, enabling the continuous segregation of highly specific polymer fractions. However, it must be noted that isolating specific colors, such as separating blue from green PET, remains an advanced capability requiring specialized multi-stage architectures; conventional baseline operations generally limit color sorting at high throughputs to separating transparent from mixed color streams.

The escalating integration of sensor-based automated systems redefines the future development of recycling infrastructure, driving the transition toward digitized, Industry 4.0 material hubs. Transitioning to fully automated systems requires substantial initial capital expenditures (CAPEX) but minimizes long-term operational expenses (OPEX) by eliminating manual labor dependencies and maximizing output purity. Furthermore, implementing deep convolutional neural networks and hyperspectral data streams establishes the computational capacity to dynamically adapt to fluctuating input stream variables, including material humidity and organic matter adhesion. The trend toward intelligent vision systems and robotic sorting arms signifies that future facilities will operate as modular, decentralized units capable of generating continuous chemical traceability data, an essential prerequisite for feeding downstream advanced chemical recycling reactors.

The economic viability of material recovery facilities relies fundamentally on municipal source separation protocols, regional waste compositions, and localized energy costs. Technoeconomic literature exhibits methodological gaps, restricting financial analyses to primary target products and masking actual disposal costs associated with contaminant by-product streams. Future research must integrate dynamic life-cycle assessment (LCA) algorithms with real-time automated sorting data to establish standardized financial evaluation frameworks. Ultimately, deploying sensor-driven sorting infrastructure and formulating public–private co-investment models constitute the fundamental mechanisms to mitigate landfill accumulation, prevent environmental polymer contamination, and sustain the strict material requirements of the global circular economy.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/pr14071144/s1, Figure S1: Flow diagram representing the literature selection process. Stages encompass the identification of 833 records from databases, screening based on titles and abstracts, eligibility assessment through full text analysis, and final inclusion. The diagram details the exclusion reasons, such as focus on macroscopic waste management policies, life cycle assessments, or general circular economy frameworks, yielding 79 total publications for the qualitative synthesis; Table S1: Overview of recent patent applications related to plastic waste sorting. Table S2: Technical overview of mechanical and physical sorting technologies, detailing separation principles, operational and performance metrics; Table S3: Technical specifications of sensor-based and spectroscopic sorting methods.

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Abbreviations

The following abbreviations are used in this manuscript:

ABS	Pol(acrylonitrile-co-butadiene-co-styrene)
AI	Artificial Intelligence
ANNs	Artificial Neural Networks
CAPEX	Capital Expenditures
CNNs	Convolutional Neural Networks
CO_2	Carbon dioxide
EUR	Euro currency
Fe_3O_4	Iron (II, III) oxide
FTIR	Fourier-transform infrared spectroscopy
HDPE	High-density polyethylene
HSI	Hyperspectral Imaging
IoT	Internet of Things
kNN	k-Nearest Neighbors
LCA	Life-Cycle Assessment
LDA	Linear Discriminant Analysis
LDPE	Low-Density polyethylene
LIBS	Laser-Induced Breakdown Spectroscopy
LLDPE	Linear Low-Density polyethylene
MIR	Medium Wave Infrared
MRFs	Materials recovery facilities
MSW	Municipal solid waste
NdFeB	Neodymium Iron Boron
NIR	Near-Infrared Spectroscopy
NPV	Net Present Value
OPEX	Operational Expenses
PBST	Poly(butylene succinate-co-terephthalate)
PC	Polycarbonate
PCA	Principal Component Analysis
PCL	Polycaprolactone
PE	Polyethylene
PET	Poly(ethylene terephthalate)
PHBV	Poly(hydroxybutyrate-co-valerate)
PLA	Poly(lactic acid)
PLS	Partial least squares
PMMA	Poly(methyl methacrylate)
PP	Polypropylene
PS	Polystyrene
PTFE	Polytetrafluoroethylene
PVC	Poly(vinyl chloride)
R&D	Research and Development
RDF	Waste-derived fuel
RF	Random Forests

ROI	Return On Investment
RSS	Raman Scattering Spectroscopy
SVM	Support Vector Machine
USA	United States
USD	Dollar currency
Vis	Visual Spectroscopy/Frequency
WIPO	World Intellectual Property Organization
XRF	X-Ray Fluorescence

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