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Optimization of Sensor Network for Automated Chip Sorting and Carbon Emission Reduction: Fuzzy Analytic Hierarchy Process-based Decision-making

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The miniaturization and increasing material complexity of semiconductor packaging necessitate advanced automated systems for sorting abnormal chips. Although sensor networks in the system enable a high-throughput method for separation, the optimal configuration is a multicriteria engineering challenge owing to trade-offs among hardware sensitivity, computational latency, and deployment costs. In this study, we present an integrated optimization framework based on the fuzzy analytic hierarchy process (FAHP) to configure a multisensor sorting system for recycling abnormal chips. Supporting green manufacturing through resource-efficient sensor deployment and lower energy consumption. By integrating expert judgments and operational field data in FAHP, the framework balances interdependent parameters across sixteen indicators to identify the optimal sensor network distribution. Validation results of the framework on an operational micro-semiconductor sorting line showed that the FAHP-optimized sorting system improved defect classification precision from 89.4 to 98.1%. The system also reduced data-processing queues and lowered localized edge-inference latency to 0.18 s per item, maintaining continuous power consumption below 2.0 W. This framework applies symbolic decision analysis to a cyber-physical sensor network, leading to the development of a reproducible methodology for optimizing resource-constrained manufacturing environments.

1. Introduction

The rapid growth of semiconductor manufacturing has increased the amount of abnormal chips, creating urgent demands for efficient recycling. Traditional manual or mechanical separation methods are inadequate because they cannot be used for extremely miniaturized chips and their complex components. Therefore, automated chip-sorting systems that employ multimodal sensor fusion and combine computer vision, NIR spectroscopy, and inductive metal sensing are used as a high-throughput solution for the real-time identification of abnormal chips and material separation.(1)

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Automated chip-sorting systems must have a high detection accuracy, low power consumption and deployment costs, and process stability even under high-speed industrial operations. Furthermore, modern semiconductor manufacturing increasingly demands that automated lines optimize their carbon footprint, linking operational efficiency directly to green manufacturing initiatives and CO_2 mitigation strategies. Therefore, to establish the appropriate sorting process, multicriteria decision analysis methods, particularly the fuzzy analytic hierarchy process (FAHP), are used.[2–5] FAHP incorporates fuzzy set theory for uncertainty and linguistic evaluations of accuracy and cost.[6] Such an incorporation enables decision-makers to balance technical feasibility, economic viability, and environmental sustainability when selecting appropriate technologies.

In an automated chip-sorting line, each sensor is used to monitor a distinct physical property of manufactured micro-semiconductors to isolate abnormal chips. High-speed optical computer vision systems are used to capture spatial features and identify dimensional deviations, surface fractures, and structural alignment defects on a micrometer scale. Concurrently, NIR spectroscopy is used to analyze the unique material reflectance of the chips to distinguish between various high-value polymers, ceramics, and substrates that look identical when viewed through a standard visual camera.[7] To prevent optical occlusion from industrial dust and debris, inductive metal sensors and eddy current arrays are integrated to detect underlying metallic trace compositions and different metals, such as copper, gold, and silicon distributions, without physical contact.[8]

However, implementing diverse sensor deployment in a high-speed manufacturing facility presents significant constraints. Although classification accuracy is significantly improved by maximizing the resolution of cameras and expanding the spectral bands of NIR sensors, such sensors increase data processing latency.[9] This latency often exceeds the capacity of standard edge-AI processing units, resulting in sorting bottlenecks and missed abnormal chips during high-throughput conveyor operations. In contrast, reducing sensor sensitivity, cost, and power consumption might compromise the purity of the sorted material. Furthermore, the harsh environmental conditions of a recycling plant, characterized by high vibration and thermal fluctuations, exacerbate sensor calibration drift and hardware degradation, leading to real-time classification errors. Such problems require the deployment optimization of sensors in the system using appropriate software as well as multicriteria decision-making methods.

The decision to adopt a dense sensor-fusion matrix, an isolated vision-centric sensor node, or a high-precision spectral method is not straightforward, as each option demands trade-offs across data-acquisition latency, environmental robustness, and capital expenditure. These interdependent factors make conventional evaluation approaches inadequate, since they cannot fully capture the uncertainty and subjectivity inherent in engineering judgments. In this context, FAHP can be adopted. By converting vague linguistic engineering constraints and subjective operational priorities into quantifiable weights, FAHP provides a flexible decision-making framework. The results of FAHP can be used to ensure that sensors are deployed in a technically sound way, aligning with economic feasibility and long-term operational reliability, transforming abstract trade-offs into actionable design strategies.

In this study, FAHP was applied to optimize the selection and architectural parameters of automated sensor systems for abnormal chip sorting. By reframing evaluation criteria into sensor-driven dimensions, such as spectral resolution, inductive sensitivity, energy efficiency, and sensor-fusion reliability, the results of FAHP were applied to evaluate line-scan cameras, eddy current sensors, and spectroscopic modules as candidate technologies and guide their deployment in an automated sorting system.[10–13] The results of this study provide a reference for sensor configuration choices in an automated chip-sorting system.

2. Background Knowledge

2.1 FAHP

Analytic hierarchy process (AHP) is a systematic decision-making method that decomposes complex problems into hierarchical structures and derives weights through pairwise comparisons. Although AHP is effective, it struggles with uncertainty in expert judgments because it requires numerical inputs. FAHP was developed to address this limitation by integrating fuzzy numbers for qualitative and quantitative assessments of parameters such as energy consumption and detection accuracy.[14–16] FAHP employs eigenvalues and fuzzy weights to ensure logical consistency and accommodate ambiguity for the evaluation of sensor networks for which performance metrics are expressed in relative or qualitative terms.[17–19]

2.2 Abnormal chips

Abnormal chips are characterized by material diversity, including metals, plastics, and ceramics, as well as toxicity originating from heavy metals and volatile organic compounds. In the context of high-speed production and recycling lines, an abnormal chip is defined as having (1) structural anomalies, which include micrometer-level packaging fractures, surface contamination, and dimensional deviations, (2) compositional misalignments, representing variations in the core substrate matrix, such as discrepancies in ceramics or polymers, and (3) metallurgical defects, including underlying distribution errors of metallic trace compositions such as copper, gold, and silicon.[20] Miniaturization and high integration density complicate the dismantling and recycling of these abnormal chips. Despite its recycling potential, several challenges exist in effective management, including immature recycling technologies, high economic costs, regulatory gaps, and limited public awareness.[21,22] To address these challenges, sensors capable of fine-grained detection and classification under industrial constraints are required.

Recent advances in embedded AI chips and heterogeneous computing architectures that integrate central processing units (CPUs), graphics processing units (GPUs), and neural accelerators enable real-time sensor data fusion. Automated chip-sorting systems combine line-scan cameras for high-resolution optical inspection, eddy current sensors for noncontact metal detection, and spectroscopic sensors for material composition analysis. In the system, FAHP is used to identify evaluation indicators, such as environmental impact, economic benefit, technical feasibility, and social acceptance, and sensor performance metrics. For example, energy consumption corresponds to chip-level power efficiency, and classification accuracy to sensor-data-fusion reliability. By using FAHP, a rigorous decision-making model can be established to formulate sensor selection and deployment strategies for automated sorting systems that are technically robust, economically viable, and environmentally sustainable.[23,24]

3. Methodology

3.1 FAHP

FAHP was employed in this study to optimize sensor deployment and evaluate the operational efficiency of automated sorting systems for abnormal chips. Industrial sorting requires balancing conflicting factors such as sensing accuracy, data-acquisition latency, cost, and environmental constraints.[25] In FAHP, fuzzy logic is used to translate qualitative engineering judgments, such as high robustness against optical occlusion or moderate edge-AI latency, into computable intervals and decompose multitiered constraints into hierarchical vectors with weights. By using this method, structural clarity is maintained, resolving ambiguity and maintaining reproducible engineering priorities.[26]

To ensure the reliability of FAHP, we invited experts with diverse backgrounds to evaluate the criteria, validate the pairwise comparisons, and provide consistent judgments. Their collective input was used to transform qualitative judgments into quantifiable weights, capturing industrial experience and theoretical knowledge.

- Sensors and optoelectronic system engineers (n = 5) specializing in machine vision, NIR spectroscopy, and electromagnetic induction arrays
- Embedded AI and signal processing engineers (n = 4) specializing in automation software and edge computing
- Semiconductor quality control and operations managers (n = 3) specializing in plant management and operation

By aggregating their evaluations into triangular fuzzy numbers, variances across expert opinions were processed to calculate weights. Then, FAHP was used to link sensor specifications, edge-computing latency profiles, and cost boundaries to a unified optimization model. By reducing bias and capturing uncertainty, the result of FAHP was used to select appropriate sensors with technical feasibility and long-term reliability in harsh industrial environments. The experts' evaluation results through expert questionnaires, sorting line experiments, and real-time sensor data analysis were used to confirm stability and deployment viability. The FAHP framework was organized into four levels in this study: (1) the goal level to identify and deploy the optimal automated sensor sorting system, (2) the criteria level to ensure environmental and operational durability, economic constraints, sensing and algorithmic feasibility, and system lifecycle integrity, (3) the indicator level to identify engineering metrics under four criteria, and (4) the alternative level to configure sensor deployment (Table 1).

Table 1
Criteria, indicators, and alternatives in FAHP.

Criteria	Indicator	Alternative
Environmental and operational durability (C1)	C11: Thermal stability range C12: Particle occlusion vulnerability C13: Vibration dampening C14: Continuous power consumption	A1 Multimodal fusion architecture: Optical cameras + NIR spectroscopy + eddy current loops
Economic constraints (C2)	C21: Sensor hardware capital expense C22: Algorithmic maintenance cost C23: Calibration downtime loss C24: System integration payback period	A2 Deep learning vision node: High-resolution cameras + GPU-based edge-AI
Sensing and algorithmic feasibility (C3)	C31: Sensor measurement resolution C32: Edge processing latency C33: Classification precision C34: Multisensor synchronization error	A3 Spectroscopic profiling array: X-ray fluorescence + Laser-induced breakdown spectroscopy
System lifecycle integrity (C4)	C41: Mean time between sensor failures C42: Protocol compatibility C43: Sensor-fusion modularity C44: Automation sync rate	A4 Binary proximity array: Capacitive + inductive proximity sensors

3.2 Sensor network architecture

For the real-time identification of abnormal chips, a high-throughput cyber-physical sensor network is used. The network comprises distributed, multitiered sensing nodes that capture the distinct physical and metallurgical properties of chips manufactured as they move along a high-speed industrial conveyor system. The sensing station is divided into three acquisition zones, each housing specialized hardware designed to mitigate industrial interference such as dust occlusion and mechanical vibration (Fig. 1).[27]

- High-speed spatial vision layer: A top-mounted, high-resolution linescan industrial camera with coaxial light-emitting diodes is used to capture micrometer-level spatial and geometric features. This layer isolates structural abnormalities by capturing reflected visual data to detect package microfractures, surface contamination, and minor edge alignment or dimensional deviations on the chip's surface. This layer includes a top-mounted, high-resolution monochrome line-scan industrial camera (resolution of 8192 × 1 pixels, pixel size of 7 × 7 µm, and maximum line rate of 50 kHz) paired with a high-intensity coaxial light-emitting diode array. Suspended precisely 300 mm vertically above the initial conveyor segment, this camera captures micrometer-level spatial and geometric features to isolate structural abnormalities, package microfractures, and dimensional deviations on the moving chip surfaces.
- Spectroscopic material identification layer: An inline NIR spectrometer is used to collect spectral reflectance signatures. This layer targets compositional abnormalities by utilizing molecular absorption bands to differentiate between visually identical but chemically distinct materials, separating standard silicon matrices from high-value polymers and underlying ceramic compounds. The NIR spectrometer is installed 450 mm below the camera station. The unit is built around an InGaAs linear image sensor array operating across a spectral

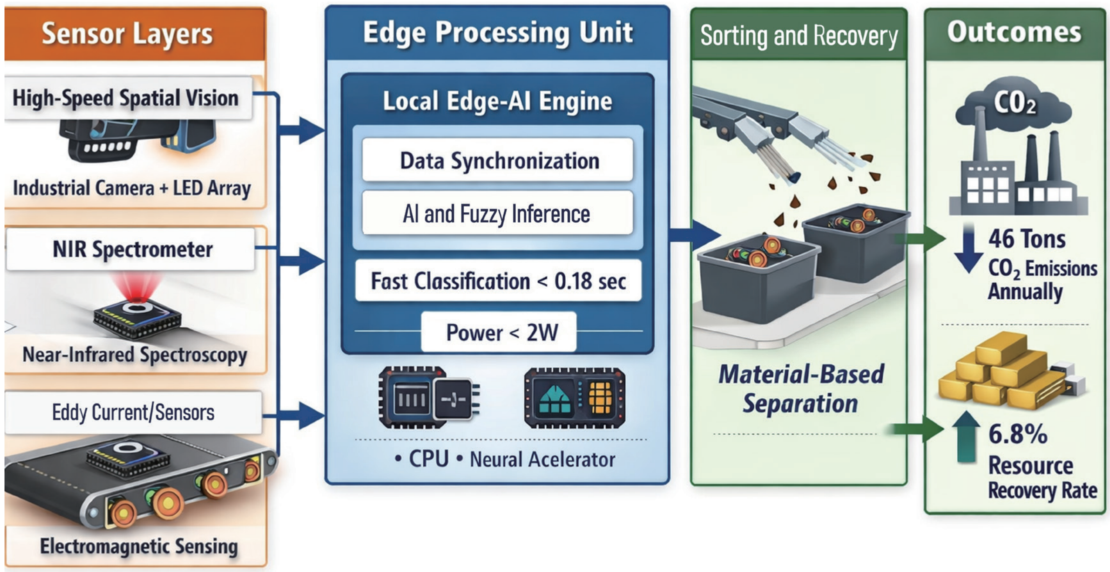

Fig. 1. (Color online) Sensor network architecture and automated sorting process (created using AI).

range of 900–1700 nm with an optical resolution of 5 nm. The unit is equipped with a focused halogen illumination module angled at 45° relative to the belt plane; it collects unique spectral reflectance signatures to differentiate polymers, silicon matrices, and ceramic compounds on the basis of distinct molecular absorption bands.

- Contactless electromagnetic sensing layer: A custom eddy current sensor array and high-frequency inductive proximity loops are embedded in the conveyor belt to measure magnetic field variations. This layer addresses metallurgical abnormalities by inducing localized eddy currents within nonmagnetic and magnetic conductors to determine the distributions of subsurface trace metals, such as copper, gold, and aluminum, and identify internal voids or metallic integrity loss, bypassing external dust accumulation. A custom-built differential eddy current sensor array was installed at the final inspection zone, 900 mm from the origin, embedded directly beneath the nonconductive conveyor belt matrix (a clearance distance of 2.0 mm). Operating at a dual excitation frequency of 500 kHz and 2 MHz via integrated high-frequency inductive proximity loops, the sensor array continuously measures magnetic field variations to map subterranean trace metal distributions independently of surface dust or debris accumulation.

To sustain continuous manufacturing speeds, raw data packets from the heterogeneous sensor network are processed locally through an edge-computing engine rather than cloud servers. Hardware-level synchronization is conducted to ensure that spatial images, spectral bands, and inductive signals from a single chip are bound to the same timestamp. These synchronized packets are processed by an embedded edge-AI accelerator integrating a low-power CPU and a neural network accelerator. Localized deep learning models and fuzzy inference engines are used for the acquisition-to-inference loop of <0.18 s per item, whereas specialized neural accelerators keep continuous power consumption below 2 W, meeting strict constraints for remote or power-limited factory environments. Once the edge classifier detects a chip as abnormal, a digital output module coordinates the timing of a high-speed pneumatic actuator grid at the end of the line. Targeted air jets deflect rejected chips into reclamation bins based on material profiles derived from the FAHP weight model.

3.3 Data acquisition

To validate the performance of the FAHP-optimized sensor network, experiments were conducted on an operational micro-semiconductor sorting line operating at a continuous conveyor belt speed of 1.5 m/s. A total dataset of 10000 microchip samples, including conforming units and preverified abnormal chips, was passed through the three sequential inspection zones. Data were collected in a centralized hardware-level synchronization framework to prevent data-packet misalignment at high speeds. A master trigger generator coupled to a rotary shaft encoder on the conveyor belt emitted precise spatial pulses. When a chip entered the initial zone, the monochrome line-scan camera was triggered via an external transistor–transistor logic (TTL) signal to capture spatial features. As the target chip passed down the line, delayed hardware interruptions triggered the NIR spectrometer and the differential eddy current sensor array at 450 and 900 mm, respectively, appending a unified hardware timestamp to all three multimodal streams. Data were captured on a local peripheral component interconnect express interface by using the embedded edge-AI accelerator engine for classification within the 0.18 s processing window. The experimental procedure comprised the following steps.[28]

- Feeding and initialization: Chips are isolated on the nonconductive conveyor belt matrix.
- Sequential inspection: As the chip passes through the 1.2 m sensing station, the master trigger generator emits precise spatial pulses. The monochrome line-scan camera executes visual inspection at the first zone through an external TTL trigger. Delayed hardware interruptions activate the inline NIR spectrometer at 450 mm and the differential eddy current sensor array at 900 mm downstream, binding all data streams to a unified hardware timestamp.
- Edge inference computation: The data are routed over a local peripheral component interconnect express interface to the local edge-AI engine. The local processor calculates the fuzzy evaluation weights and assigns a defect classification profile.
- Pneumatic separation execution: Conforming chips pass through to the primary collection area, while chips labeled as abnormal are tracked down the remaining length of the belt. Upon arrival at the end of the line, a digital output module triggers a high-speed pneumatic actuator grid. Pressurized air pulses at 4 MPa are used to divert abnormal units into designated reclamation bins, sorted according to their material category.
- Post-sort inspection: All sorted chips are manually inspected again to verify final classification precision and resource recovery rates.

4. Results

The integration of FAHP into the automated chip sorting system contributed to significant improvements across all critical performance dimensions. Before the system optimization with FAHP, sensors were selected and configured heuristically, leading to variability in accuracy, latency, and energy consumption. In contrast, FAHP results were used to balance environmental durability, economic constraints, sensing feasibility, and lifecycle integrity, resulting in a robust and reproducible deployment strategy. Trials on the chip sorting line showed that the FAHP-guided sensor network achieved 98.1% classification accuracy, 0.18 s inference latency per item, and <2 W continuous power consumption. These results showed substantial gains compared with those of the system without FAHP optimization (Table 2).

By upgrading from conventional mechanical separation to the FAHP-optimized sorting system, the industrial deployment showed an annual reduction of approximately 46 tons of CO_2 emissions per line, achieved through reduced reprocessing and improved energy efficiency. Concurrently, the precision of the sensor array elevates the overall resource recovery rate by 6.8%, preventing high-value metals from being lost to contaminated scrap streams and demonstrating a direct link between smart sensor deployment and sustainable engineering practices. Beyond sensor deployment, FAHP was also applied to evaluate alternative recycling schemes for abnormal chips. The fuzzy evaluation scores reflected performance across environmental, economic, technological, and lifecycle criteria.

The FAHP results showed that bioleaching combined with green extraction (A4) is the most favorable recycling option, having a defuzzified score of 0.692. This shows that environmentally friendly methods, which reduce CO_2 emissions and enjoy high public acceptance, outperform traditional methods when evaluated across multiple criteria. However, the relatively low technological maturity of bioleaching means that phased deployment and further research are required before it can be widely adopted. Chemical dissolution with electrolytic recovery (A1) scored 0.672, which is close to A4. This indicates that technological stability and readiness are more important than innovation. In such cases, A1 is preferred because it offers proven reliability and lower technical risk.

Mechanical crushing and physical separation (A3) scored 0.647, reflecting its advantages in cost efficiency and operational simplicity. This makes A3 well suited to investment-constrained scenarios where budget limitations are a priority. However, its lower precision and weaker environmental performance limit its long-term sustainability impact, meaning it is best used as a

Table 2
Performances of automated chip-sorting systems.

Metric	System without FAHP optimization	Optimized system with FAHP optimization	Improvement
Classification accuracy	92.40%	98.10%	+5.7%
Processing speed	0.42 s/item	0.18 s/item	2.3 times faster
Power consumption	6.5 W	<2 W	−69%
Resource recovery rate	84.70%	91.50%	+6.8%
Annual CO_2 reduction	—	46 metric tons/line	Sustainability gain

transitional or preliminary step rather than a comprehensive solution. High-temperature smelting (A2) scored the lowest at 0.583. This result shows its disadvantages, including high energy consumption, environmental risks, and reduced efficiency. Despite these drawbacks, A2 remains applicable in large-scale centralized treatment facilities where throughput requirements outweigh sustainability concerns (Table 3).

Bioleaching (A4) and chemical dissolution (A1) are relatively close in score, suggesting that both are viable depending on context. Mechanical separation (A3) shows a clear advantage over smelting (A2), reinforcing the idea that A2 is the least competitive option under the FAHP framework. These results imply that bioleaching is the most sustainable path forward, but chemical dissolution remains a strong alternative for stability-focused applications. Mechanical separation is valuable for cost-sensitive deployments, whereas smelting is relegated to niche, large-scale scenarios. Hybrid methods, such as mechanical presorting followed by bioleaching or chemical dissolution, can maximize the environmental and economic recycling of abnormal chips sorted by the automated chip-sorting system.

5. Discussion

The prioritization of bioleaching with green extraction (A4) shows that environmentally friendly recycling methods outperform traditional approaches when evaluated across multiple criteria. This implies that sensor technologies must evolve to support biological monitoring, including pH measurement, microbial activity tracking, and leaching efficiency assessment. Such sensors will enable phased deployment of bioleaching while ensuring process stability and environmental compliance.[29] The performance of chemical dissolution with electrolytic recovery (A1) shows the trade-off between innovation and reliability. When technological stability is prioritized, chemical dissolution is preferred despite its slightly lower sustainability. This indicates that sensor deployment strategies must be formulated to enhance robustness, calibration stability, and lifecycle. Sensors with enhanced durability and standardized communication protocols need to be developed to support chemical recovery processes at scale.[30]

Table 3
FAHP ranking of recycling schemes.

Alternative and effect	Fuzzy synthetic index	Defuzzified score	Rank
A4 Bioleaching + green extraction	(0.532, 0.692, 0.852)	0.692	1st
A1 Chemical dissolution + electrolytic recovery	(0.512, 0.672, 0.832)	0.672	2nd
A3 Mechanical crushing + physical separation	(0.487, 0.647, 0.807)	0.647	3rd
A2 High temperature smelting	(0.423, 0.583, 0.743)	0.583	4th

The role of mechanical crushing and physical separation (A3) as a cost-efficient option suggests that sensor networks must adapt to investment-constrained environments. In such scenarios, simplified sensor arrays with lower capital expenditure but adequate precision provide practical solutions. This leads to the development of modular, scalable sensor systems deployed incrementally and later integrated with advanced spectroscopy or AI-based sorting.[31] The relatively poor performance of high-temperature smelting (A2) under the FAHP framework reflects its environmental and energy disadvantages. Nevertheless, its continued relevance in large-scale centralized treatment shows that sensors must operate under extreme thermal and electromagnetic conditions. This necessitates investment in high-temperature-resistant sensors and robust data acquisition systems that can withstand harsh industrial environments while minimizing energy overhead.[32]

The results of this study show that FAHP can be used to formulate a structured sensor deployment strategy with priorities in abnormal chip recycling. Sensor deployment strategies must be context-sensitive, and sensor configurations that balance accuracy, latency, cost, and sustainability should be selected. Modularity, environmental compatibility, and lifecycle resilience must be prioritized to ensure that sensor networks can adapt to green technologies and related industrial processes. By linking advanced sensors to abnormal chip recycling strategies, technical feasibility with sustainability goals can be achieved.[33]

6. Conclusions

We deployed a multicriteria decision-making framework to optimize the architecture of automated sensor networks for high-speed abnormal chip sorting. By combining FAHP, the framework resolved engineering uncertainties, reduced operational noise, and balanced hardware and software trade-offs that often complicate multimodal sensor configurations in recycling environments. Instead of focusing on abstract reclamation methods, the model provided a clear way to evaluate sensing feasibility, data-processing latency, power use, and durability at the same time. Validation trials on an active semiconductor sorting line confirmed the value of the framework. Compared with conventional single-sensor systems, the FAHP-optimized sensor network showed significant improvements. Defect classification accuracy increased from 89.4 to 98.1% by integrating a NIR spectrometer with a line-scan camera to capture subsurface signals. Inference speed improved as latency decreased from 0.42 to 0.18 s per item, owing to hardware-level synchronization that avoided software bottlenecks. Energy efficiency increased, with power consumption reduced to below 2.0 W compared with 4.8 W in unoptimized systems. Finally, resource recovery improved by 6.8%, supporting an annual reduction of about 46 metric tons of CO_2 emissions per line.

Traditional sensor deployment strategies rely on intuition or isolated calibration, which fail under real-time multimodal conditions. In contrast, the deployed framework enables a reproducible method that translates qualitative experience into measurable device parameters. FAHP is used as a pre-hardware compiler to predict latency, occlusion risks, and power limits before installation. The synchronization of vision, spectroscopic, and inductive sensors on a single low-power edge module can be used in resource-constrained industrial IoT applications. The deployed framework contributes to the development of autonomous and resilient sorting networks and enables miniaturized electronic waste to be handled with high accuracy, efficiency, and sustainability, directly supporting the goals of modern sensor technology development.

References

1 A. Khoshand, K. Rahimi, M. Ehteshami, and S. Gharaei: Environ. Sci. Pollut. Res. Int. **26** (2019) 9649. https://doi.org/10.1007/s11356-019-04407-8
2 C.-H. Yeh and Y. Xu: J. Clean. Prod. **52** (2013) 194. https://doi.org/10.1016/j.jclepro.2013.03.003
3 M. R. Seikh and P. Chatterjee: Eng. Appl. Artif. Intell. **135** (2024) 108701. https://doi.org/10.1016/j.engappai.2024.108701
4 P. Sirisawat and T. Kiatcharoenpol: Comput. Ind. Eng. **117** (2018) 303. https://doi.org/10.1016/j.cie.2018.01.015
5 Q. Wang, H. H. Lin, H. L. Siek, and S. Y. Wang: Sens. Mater. **38** (2026) 2245. https://doi.org/10.18494/SAM6267
6 M. Narang and V. Bhardwaj: Proc. Research, Innovation, Knowledge Management and Technology Application for Business Sustainability (INBUSH, 2020) 226. https://doi.org/10.1109/INBUSH46973.2020.9392167
7 A. M. Kumaran, R. Elagib, A. De Iacovo, A. Ballabio, J. Frigerio, G. Isella, G. Assanto, and L. Colace: Appl. Sci. **15** (2025) 8964. https://doi.org/10.3390/app15168964
8 Y. Shao, Z. Xia, Y. Ding, B. Crocker, S. Saunders, X. Bai, A. Peyton, D. Conniffe, and W. Yin: Sensors **24** (2024) 4216. https://doi.org/10.3390/s24134216
9 S. Chung, J. Lim, K. J. Noh, G. Kim, and H. Jeong: Sensors **19** (2019) 1716. https://doi.org/10.3390/s19071716
10 M. Keshavarz-Ghorabaee, M. Amiri, E. K. Zavadskas, Z. Turskis, and J. Antucheviciene: Sustainability **14** (2022) 10371. https://doi.org/10.3390/su141610371
11 H. Dinçer, S. Yüksel, and Z. Karpyn: Waste Manag. Res. **43** (2024) 3. https://doi.org/10.1177/0734242X241242682
12 B. Ijaz, S. Narayanamoorthy, M. Sandra, N. Almakayeel, H. Dincer, S. Yuksel, and D. Kang: Sci. Rep. **16** (2026) 2006. https://doi.org/10.1038/s41598-025-31734-3
13 M. Yazdani, C. Ye, M.T. Shaayesteh, and P. Zaraté: Int. J. Prod. Manag. Eng. **13** (2025) 1. https://doi.org/10.4995/ijpme.2025.21558
14 M. A. Darzi: J. Environ. Manag. **373** (2025) 123999. https://doi.org/10.1016/j.jenvman.2024.123999
15 B. G. Demircan and K. Yetilmezsoy: Sustainability **15** (2023) 6526. https://doi.org/10.3390/su15086526
16 S. Singh, M. S. Dasgupta, and S. Routroy: Waste Manag. Res. **40** (2021) 5. https://doi.org/10.1177/0734242X211018512
17 M. S. Habib and S.-J. Hwang: Appl. Soft Comput. **176** (2025) 113097. https://doi.org/10.1016/j.asoc.2025.113097
18 M. Kim, Y.-C. Jang, and S. Lee: J. Environ. Manag. **128** (2013) 941. https://doi.org/10.1016/j.jenvman.2013.06.049
19 H. B. Bolat, İ. Otay, G. T. Temur, and Ş. İmre: Int. J. Fuzzy Syst. Appl. **10** (2021) 21. https://doi.org/10.4018/IJFSA.2021040102
20 Y. Jiang, Z. Zhang, Z. An, X. Pan, X. Shi, R. Wang, J. Li, C. Chen, Z. Cao, Y. Xu, J. Wei, X. Zhang, and Y. Peng: Crystals **16** (2026) 265. https://doi.org/10.3390/cryst16040265
21 H. K. Chan, X. Wang, G. R. T. White, and N. Yip: IEEE Trans. Eng. Manag. **60** (2013) 327. https://doi.org/10.1109/TEM.2012.2196704
22 A. Pavlović, D. Tadić, S. Arsovski, D. Jevtić, and M. Pavlović: Acta Polytech. Hung. **13** (2016) 7. https://acta.uni-obuda.hu/Aleksandar_Danijela_Slavko_Dragan_Milan_71.pdf.
23 K. Karuppiah and B. Sankaranarayanan: Appl. Soft Comput. **144** (2023) 110420. https://doi.org/10.1016/j.asoc.2023.110420.
24 J.-J. Wei, H.-H. Lin, and S. L. Chen: EJMSTE **19** (2023) 2354. https://doi.org/10.29333/ejmste/13749
25 F. Jolai, M. Jahangoshai Rezaee, and A. Vazifeh: J. Intell. Manuf. **20** (2009) 113. https://doi.org/10.1007/s10845-008-0107-3
26 J.H. Lee, B.H. Kim, and M.Y. Kim: Int. J. Control Autom. Syst. **19** (2021) 3503. https://doi.org/10.1007/s12555-020-0118-1
27 T.-L. Chen, J. C. Chen, C.-F. Huang, and P.-C. Chang: Simul. Model. Pract. Theory **106** (2021) 102192. https://

doi.org/10.1016/j.simpat.2020.102192
28 Z. Xu, J. Zhang, and Y. He: Processes **10** (2022) 1020. https://doi.org/10.3390/pr10051020
29 K. Bosecker: FEMS Microbiol. Rev. **20** (1997) 591. https://doi.org/10.1016/S0168-6445(97)00036-3
30 V. Rai, D. Liu, D. Xia, Y. Jayaraman, and J.-C.P. Gabriel: Recycling **6** (2021) 53. https://doi.org/10.3390/recycling6030053
31 A. K. Awasthi and J. Li: Resour. Conserv. Recycl. **126** (2017) 228. https://doi.org/10.1016/j.resconrec.2017.07.014
32 J. Cui and L. Zhang: J. Hazard. Mater. **158** (2008) 228. https://doi.org/10.1016/j.jhazmat.2008.02.001
33 M. P. Da Cunha: Proc. IEEE Int. Ultrasonics Symp. (IUS, 2025) 1. https://doi.org/10.1109/IUS62464.2025.11201426.