

Smart Bio Waste Management System: A Review

Aditya Chanodiya, Prof. Abhishek Popat Bangar, Prof. S. B. Bhosale, Prof. Karad V. A.

Department of Computer Engineering
Jaihind College of Engineering, Kuran, Maharashtra, India

Abstract- Handling bio-waste becomes harder as cities expand, and a number of efforts now try to make the process smarter through sensors, optimization, better treatment planning and policy design. This review looks at five selected scholarly works that cover different parts of the problem: an IoT-based intelligent waste management system for smart cities, a location-allocation model for treating hotel bio-waste on site, a smart-bin study carried out in ten hospitals, a review of thirteen biowaste treatment technologies, and an edited volume on composting through nexus thinking. The literature suggests that sensing and optimization can cut energy use, data gaps and transport effort, but that these gains depend on what comes after collection: which treatment technology is chosen, where facilities are sited, whether the products can be sold, and whether policy backs the whole chain. We compare the methods and limits of the works, point out gaps, and propose directions for a smart bio-waste management system. Since the review rests on five selected works and not on a database search, it is a focused narrative review and not a systematic one.

Keywords— Smart waste management, bio-waste, Internet of Things, composting, facility location, route optimization, circular economy.

I. INTRODUCTION

Bio-waste covers everything biodegradable that homes, markets, hotels and gardens throw out, from leftover food and kitchen scraps to leaves and cuttings. Across low- and middle-income countries it is the biggest single component of municipal waste (Lohri et al., 2017). For the tourism sector, Santos-Peñate et al. (2023) refer to estimates that around half of hotel waste consists of food and garden bio-waste. A great deal of this material is still sent to landfills or open dumps, where it produces greenhouse gases rather than feeding nutrients back into soils (Hettiarachchi et al., 2020).

People often imagine a smart bio-waste system as bins fitted with sensors, a cloud platform collecting their data, and trucks that visit only the bins that need emptying. The five works examined here make clear that this covers only part of the story. Ahmed et al. (2023) design an IoT setup for smart bins that copes with sensor battery drain, gaps in readings and truck routing. Ishaq et al. (2025) put ultrasonic smart bins to work in ten Nigerian hospitals. Santos-Peñate et al. (2023) look at where a hotel group ought to install composters and pelletizers, so that waste is processed close to where it arises. Lohri et al. (2017)

set thirteen routes for converting urban biowaste into valuable products side by side, while Hettiarachchi et al. (2020) use composting case studies to claim that market conditions and policy settings determine whether treatment works.

Our aims are fourfold: (i) to summarize each selected study and what it found; (ii) to set their methods, contributions and scope against one another; (iii) to bring out the challenges and gaps that the group of papers hints at; and (iv) to suggest research paths towards a smart bio-waste management system. Note that two of the five works concern waste that is not purely organic, namely general smart-bin waste and biomedical waste. We kept them because the way they monitor and collect waste is directly useful for the smart component, and the comparison below stays aware of this difference in waste type.

II. REVIEW METHODOLOGY AND SELECTION CRITERIA

The paper is a focused narrative review built on five chosen works about bio-waste management and the technology that supports it. Each one was picked since it deals with a separate link of the chain: sensing and routing, facility siting, IoT monitoring in

the field, treatment technology, or composting policy. For every work, we compared its focus, method, key findings and the limitations it states or implies. As the review uses only the five works provided, and no full database search or formal screening was carried out, it should not be taken as a systematic review.

We read the works and arranged them by focus, method, main results and bearing on our objectives. Experimental and modelling papers were assessed by looking at their data, test conditions and the methods they were compared with. For Lohri et al. (2017), we paid attention to how technologies are grouped and how the published literature is analysed. The edited volume was handled as a set of case studies and policy debate rather than as a controlled study, and we drew mostly on its opening chapter and table of chapters; we do not claim to have studied each case chapter in depth.

Selection followed four criteria: (1) a clear link to bio-waste or to smart, sensor-driven waste handling; (2) a definable research question, model or analytical goal; (3) publication as a journal article or as a scholarly book by a recognized publisher; and (4) a bearing on at least one theme of this review. We added nothing to the five items. No search strings, multiple databases or screening stages were involved, so we make no claim of exhaustive coverage or of following PRISMA.

III. LITERATURE REVIEW

1. Intelligent waste management with IoT, imputation and routing

Ahmed et al. (2023) propose an intelligent waste management system (IWMS) for smart cities, where smart bins carry sensors and actuators. The design has three stages. Stage one groups the bins into clusters through a modified LEACH protocol (AHA-LEACH); the artificial hummingbird algorithm selects the cluster heads, which spreads energy consumption more evenly over the network. Stage two repairs gaps in the sensor data using AHA-KNN, a k-nearest-neighbour approach whose value of k is chosen by that same optimizer. Stage three applies a multi-objective variant (MOAHA) to plan truck

routes, taking into account bin energy, waste volume and odour.

According to the tests reported, ten sampled bins used on average 11,726.3 units of energy before and 7,737.4 after AHA-LEACH was applied, which agrees with the 34% saving mentioned in the abstract; bin nodes also survived for about 200 iterations, whereas competing clustering methods managed 50 to 130. In the imputation tables, AHA-KNN had the smallest RMSE when data were missing at random or not missing at random. When data were missing completely at random, however, mean imputation or ordinary KNN show errors that are similar or smaller, so the paper's general claim is not entirely supported there. MOAHA was benchmarked against seven other multi-objective algorithms, finishing 500 iterations in 146.7 s while the next quickest took 196.7 s. All experiments were done in MATLAB with one truck, and the authors admit that parameters take effort to tune and that the data are incomplete.

2. Location and allocation of bio-waste treatment

Santos-Peñate et al. (2023) formulate a mixed-integer programming model to choose which hotels in a chain should receive composters and pelletizers, and to direct food waste, soft garden waste and hard garden waste towards hotels, a farm, a local plant or the public ecopark. The resulting compost and pellets are in turn allocated to the sites that can use them. Total cost is the quantity being minimized, and it adds up capital, operating, transport, treatment, product and surplus costs.

An illustrative example with 11 hotels in Gran Canaria, eight composter types and a single pelletizer type is used to test the model. The authors generate 180 scenarios by changing the discount rate, the ecopark treatment price, the transport cost and the surplus cost. Each scenario was solved in about 0.4 s on average with GAMS and CPLEX. Their conclusion is that composters in selected hotels are a profitable investment, except where transport and treatment are very cheap and surplus cost is high. The four hotels with the most beds (1, 4, 9 and 10) were selected for composters in most scenarios, and hotel 9 was the best candidate for the pelletizer. As some of the data are simulated, the case illustrates

the workings of the model instead of forecasting what would happen in a real chain.

3. Smart bins for biomedical waste

Ishaq et al. (2025) investigate IoT smart bins as a tool for biomedical waste management in Kaduna, Nigeria. Colour-coded bins contain ultrasonic sensors that track how full they are; when a bin crosses a set threshold, an alert travels to a cloud system and on to waste collectors, who then weigh and sort the contents by hand. The data come from ten hospitals, collected in December 2022, and the hospitals were selected on the basis of stable wireless Internet. Depending on the hospital, collectors reacted to the full-bin alarms within about 3 to 16 minutes.

Between 43.62% and 52.47% of hospital waste was biomedical, and the average was 69.14 kg a day, equal to 0.74 kg per bed per day; bigger hospitals generated more. Principal component analysis is also used by the authors to explore the links between waste types and ward-level sources. The work has value since it gives field figures for a context in which dependable data on waste generation are rare. On the other hand, the sample is small, hospitals were selected for their connectivity, and no baseline without sensors is reported, which means the paper cannot show how much the IoT system itself improved things. Biomedical waste is, in addition, regulated differently from organic biowaste.

4. Treatment technologies for urban biowaste

Lohri et al. (2017) survey 13 technologies for treating urban solid biowaste, concentrating on low- and middle-income contexts. The technologies form four families: direct use (land application, animal feed, combustion); biological treatment (composting, vermicomposting, black soldier fly treatment, anaerobic digestion, fermentation); physico-chemical treatment (transesterification, densification); and thermo-chemical treatment (pyrolysis, liquefaction, gasification). For each, the authors outline what feedstock it needs, the conditions of the process, the products obtained and the difficulties it meets locally.

In addition, the authors queried Scopus for articles from 2005 to 2015 and classified a sample as process engineering, implementation or sustainability studies. Laboratory scale was where the newer or more complex options, for instance black soldier fly treatment, pyrolysis and liquefaction, were mostly examined, while composting and anaerobic digestion had more full-scale work. Across all technologies, case studies and field research were scarce. The authors maintain that a technology should be chosen only after considering the waste streams available and the market for the products, that source separation is vital for quality, and that blending several technologies is attractive but makes the system more complicated. As a wide-ranging review, it lays out options without naming the best one for any particular city, and its publication counts rest on the search terms used and on Scopus alone.

5. Composting and nexus thinking

Hettiarachchi et al. (2020), as editors, present composting as a bridge between waste management on one side and soil and agriculture on the other, through what they call nexus thinking. Their opening chapter holds that composting has fallen short of its potential chiefly because the waste and farming sectors evolved apart, and because numerous composting projects have no workable business case. Farmers may lean towards subsidized chemical fertilizer even as municipalities are urged to adopt sustainable waste handling; the editors call this a policy conflict. The chapter further connects composting with several Sustainable Development Goals, among them zero hunger, responsible consumption and production, and climate action.

Cases are presented for Cajicá in Colombia, India, Sri Lanka, Tanzania, Accra in Ghana and Versailles, and are followed by chapters on co-composting (including an Italian case) and on biochar-compost blends (including a Finnish case). As the introduction tells it, the Cajicá experience shows that a participatory approach enabled a municipality to set up a successful composting programme within a few years. The editors caution too that compost made from non-traditional inputs such as sewage sludge and manure may carry contaminants of emerging concern, for example microplastics and antibiotic

resistance determinants, and that national standards for compost quality differ greatly. Because the book is a set of cases and discussion and not a controlled comparison, its lessons need checking in every local setting.

IV. COMPARATIVE ANALYSIS OF THE STUDIES

The five works deal with linked problems at different stages of the bio-waste chain using different methods, so their results are complementary and cannot simply be swapped for one another. Table 1 summarizes the scope, main contribution and boundary of each work.

Table 1. Comparative summary of the five selected studies

Study	Method / scope	Main finding and boundary
Ahmed et al. (2023)	IoT system design; MATLAB experiments on bin energy, missing-data imputation and truck routing	Lower bin-network energy use, filled-in sensor gaps and faster routing than seven other algorithms; simulated setting, single truck.
Santos-Peñate et al. (2023)	Mixed-integer location-allocation model; 11 hotels, 180 scenarios	On-site composters pay off in most scenarios, except when transport and treatment costs are very low and surplus cost is high; data partly simulated.
Ishaq et al. (2025)	Field study with IoT smart bins in 10 hospitals; PCA	Collector response of 3 to 16 min; biomedical waste about 48% of hospital waste; small sample and no non-sensor baseline.

Study	Method / scope	Main finding and boundary
Lohri et al. (2017)	Review of 13 treatment technologies; Scopus analysis, 2005-2015	Field and case studies are scarce for every technology; choice depends on feedstock and market; Scopus only.
Hettiarachchi et al. (2020)	Edited volume of composting case studies	Sector disconnect, weak business cases and contaminant risks limit composting; case-based, not controlled.

One theme is the distance between gathering data and using it. Both Ahmed et al. (2023) and Ishaq et al. (2025) demonstrate bins that report their own status, yet neither tracks the waste after collection to a decision on treatment. Santos-Peñate et al. (2023) and Lohri et al. (2017) pick up at that later point and ask where and in what way the waste ought to be processed.

Data quality is another theme. Ahmed et al. (2023) deal with sensors that drop readings and with bin nodes whose energy must be preserved, and Ishaq et al. (2025) observe that hospitals in Nigeria mostly lack dependable figures on waste generation. Cost and distance form a third theme: routing and facility models both try to reduce transport, but the facility model reveals that the best solution moves with treatment prices, transport cost and surplus cost. Last, Hettiarachchi et al. (2020) and Lohri et al. (2017) each emphasize that technology on its own does not suffice, since products need buyers and quality hinges on source separation and helpful policy.

Method decides what a work is able to demonstrate. Simulation and optimization reveal what could be achieved under given assumptions; a sensor-based field study reports what occurs at a handful of real sites; a technology review charts the available options; and an edited volume of cases illustrates

how policy and markets work out in practice. No single approach spans the whole chain, so a firmer understanding calls for reading these methods together and applying them to local conditions.

V. RESEARCH CHALLENGES AND IDENTIFIED GAPS

The following are gaps that the five works suggest. They do not prove that nobody else has studied these questions.

1. From bin signals to treatment decisions

Across the selected works, monitoring of bins and planning of treatment are kept apart. Santos-Peñate et al. (2023) rely on yearly waste quantities in their location-allocation model, and the smart-bin studies end once waste is collected. Future work could examine whether live data on fill level and waste type can feed back into treatment and routing choices, such as directing food waste to the closest composter with free capacity.

2. Evidence from real deployments

Ahmed et al. (2023) rely on MATLAB experiments, Santos-Peñate et al. (2023) work with partly simulated data, and Ishaq et al. (2025) present field data from a brief collection window and without a baseline lacking sensors. Lohri et al. (2017) also observe a shortage of case studies and field research for each technology they cover. Longer pilot projects running at several sites and compared with current practice would offer a sounder foundation for statements about savings.

3. Reliability of sensor data

Smart-bin systems are affected by lost readings, limited energy and dependence on wireless coverage. In the RMSE results of Ahmed et al. (2023), the best-performing imputation method varies with the missingness mechanism and the share of missing data, so it is not obvious which method deserves trust on real bin data. Work on real sensor logs, with failure patterns documented, might resolve the question.

4. Costs, markets and policy

According to the facility model, whether on-site treatment is justified hinges on treatment prices, transport cost and surplus cost, and Hettiarachchi et al. (2020) demonstrate how fertilizer subsidies and absent markets can weaken composting projects. Santos-Peñate et al. (2023) account for prices and surplus costs but leave out subsidies and uncertain demand. Location models could be extended to cover uncertain prices, subsidies and product demand, then tested on real municipal or hotel data.

5. Source separation, quality and safety

Source separation is described by Lohri et al. (2017) as essential for product quality, while Hettiarachchi et al. (2020) caution about contaminants, plastics and antibiotic resistance determinants in compost. Ishaq et al. (2025) use colour-coded bins whose contents collectors separate by hand. Not one of the works checks whether sensing or feedback at the bin could improve how organic waste is separated or spot contamination before treatment, which is a practical gap for any smart bio-waste system.

VI. PROPOSED RESEARCH DIRECTIONS

On the basis of the comparison, the directions below may help tackle the challenges described:

- **Sensor-to-treatment integration:** connect real-time bin data to the choice of facility and to routing, and quantify the change in travel distance, use of treatment capacity and collection delays.
- **Field pilots with baselines:** carry out smart-bin and on-site composting pilots lasting several months at more than one location, with current collection practice as the point of comparison.
- **Robust data handling:** try imputation and fault-tolerant communication methods on real sensor logs, reporting their failure rates and energy cost.
- **Market-aware optimization:** include product demand, uncertain prices and subsidies in location-allocation models, so plans never rest on a market that is not there.
- **Source-separation support:** study whether sensing at the bin, feedback and simple guidance for users make organic waste cleaner.

- **Multi-criteria evaluation:** assess systems on cost, energy, emissions, health risk and user acceptance together, not on one measure.
- **Context-sensitive governance:** contrast municipal, private and hotel-based arrangements under varying policies, in the spirit of the nexus approach of Hettiarachchi et al. (2020).

Future studies ought to describe their data, assumptions and parameters clearly, and to keep simulated results separate from measurements taken in the field. They should report trade-offs as well, because an added sensor or safeguard may reduce risk while raising cost, energy consumption or upkeep.

VII. CONCLUSION AND FUTURE SCOPE

Five works on smart, technology-assisted bio-waste management were examined here. Taken together, they indicate that sensing and optimization can lower energy consumption in a bin network and allow fast collection responses (Ahmed et al., 2023; Ishaq et al., 2025); that facility location and cost structure determine whether treating waste on site is worthwhile (Santos-Peñate et al., 2023); that although many treatment technologies exist, field evidence for them is limited (Lohri et al., 2017); and that markets, policy and compost safety decide whether composting succeeds at all (Hettiarachchi et al., 2020).

A limitation of this review is the small, hand-picked group of five works, which does not cover the whole field. The works differ in waste type, method and setting, two of them concern waste that is not strictly organic, and one is an edited volume read mostly through its introduction, so the results cannot be treated as one uniform outcome. A broader review should query several scholarly databases, record search terms and screening decisions, and add literature on biogas and other energy routes, recent AI-based waste sorting, and life-cycle and cost assessment.

To sum up, a smart bio-waste management system performs best when sensing and optimization are

tied to treatment planning, market demand and supportive policy. Future research should concentrate on integration tested in the field, dependable data, realistic economics, and safe products of good quality.

REFERENCES

1. Ahmed, M. M., Hassanien, E., & Hassanien, A. E. (2023). IoT-based intelligent waste management system. *Neural Computing and Applications*, 35, 23551–23579. <https://doi.org/10.1007/s00521-023-08970-7>
2. Hettiarachchi, H., Caucci, S., & Schwärzel, K. (Eds.). (2020). *Organic waste composting through nexus thinking: Practices, policies, and trends*. Springer. <https://doi.org/10.1007/978-3-030-36283-6>
3. Ishaq, A., Mohammad, S. J., Bello, A. D., Wada, S. A., Adebayo, A., & Jagun, Z. T. (2025). Smart waste bin monitoring using IoT for sustainable biomedical waste management. *Environmental Science and Pollution Research*, 32, 19434–19449. <https://doi.org/10.1007/s11356-023-30240-1>
4. Lohri, C. R., Diener, S., Zabaleta, I., Mertenat, A., & Zurbrugg, C. (2017). Treatment technologies for urban solid biowaste to create value products: A review with focus on low- and middle-income settings. *Reviews in Environmental Science and Bio/Technology*, 16, 81–130. <https://doi.org/10.1007/s11157-017-9422-5>
5. Santos-Peñate, D. R., Suárez-Vega, R. R., & Florido de la Nuez, C. (2023). A location-allocation model for bio-waste management in the hospitality sector. *Networks and Spatial Economics*, 23, 611–639. <https://doi.org/10.1007/s11067-023-09593-0>