IoT based Smart Waste Management Using Deep Reinforcement Learning

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Abstract. Ever-increasing need for improving the livability of a city and improve outcomes for its residents, over the last decade, the adoption of technology to develop urbanised societies around the world has given rise to the need for developing smart cities. The speed at which the world population is growing, the use of Internet of Things in smart cities have really advanced the quality of life. One significant area of concern within the smart city framework is waste management. If the waste within a city is not adequately managed, then it leads to issues in the health of the citizens. Additionally, the waste management has such a high impact on the environmental footprint, hence the need to have a smart way of managing waste is of critical importance. Through our research, we analyse the challenges of waste management within a city to understand the impact of the problem on to the citizens and overall city operations. We then investigate ways in which we can solve these problems using the emerging technologies, such as the Internet of Things, to collect valuable data of large volumes arriving at an astronomical rate, then apply multi-agent deep reinforcement learning algorithms to harness the power of big data to extract meaningful information and actionable insights. We ingest data generated by our Internet of Things into our algorithm for three main purposes including providing the notifications to an external system, for example, a map navigation engine out of the scope for this project but a future extension for route optimisation and waste vehicle tracking; extracting and reporting the actionable insights from the underlying data; and consuming the extracted data for predictive forecasting to draw out the unknown patterns of waste fill levels within various geographical locations and again send out triggers and notification to external systems for example a waste collection authority who can efficiently schedule the waste collection vehicles and optimise the route. To achieve the above mentioned outcomes, we propose a framework that is agnostic of the hardware that it connects to and can effectively interface with a wide variety of hardware keeping a level of abstraction in the architecture.

Keywords: sustainability; smart cities; Internet of Things (IoT); multi-agent deep reinforcement learning; smart waste management; smart sensors

1 Introduction

Over the last decade smart cities have helped save 30–300 lives each year in a city of 5 million, helped reduce crime incidents by 30–40%, decreased disease burden by 8–15%, saved time in daily commute by 15–30 minutes, reduce solid wastes, saved water consumption per person per day by 25–80 litres, and reduced emergency response times by 20–35% [1]. In order to meet the challenges and improve the quality of service delivery to the citizens, the smart cities across the world make use of information and communication technologies to build a seamlessly interconnected society [2]. More compelling arguments suggest that the smart city concept not only improves the outcomes of services for the citizens but also empowers the governments to use modern technology for the effective and efficient running of their public administration [3].

According to Neirotti et al., "it is expected that global smart city market will exceed US$1200 billion by 2024, which is almost triple that in 2014" [4]. According to the latest United Nations Population Fund, approximately more than half of the world's population presently lives in urban areas. A prediction that approximately 66 percent of the world's population will live in an urban environment by 2050 [5].

In the recent times, the term "smart city" is being interchangeably used with the terms "intelligent city" and "digital city". A number of researchers have given various definitions for smart city, however, the one that touches on the key aspects and objectives of the smart city is from Fernández-Isabel and Fuentes-Fernández: "The basic need to have a smart city is the intersection of a sustainable environment the quality of life and the cost of living. The intelligence lies in the way we inculcate the concept of smart intelligence." [6].

1.1 Smart Waste Management

The hyper connected smart cities across the globe have undertaken various digital, intelligent and smart initiatives on various scales and of different complexities. It has been observed that the applications modernisation is not merely a process of selecting the technological solutions to automate the processes; but it is a blend of technology and functional techniques & methods to build digital assets. One of the biggest areas of smart city improvement lies within the smart waste management. Our research aims to propose a robust framework for smart waste management using a methodical approach in form of stages of transformation using key technologies such as IoT, Data Mining and Machine Learning. The research aims to focus on both the technical areas and the functional aspects of the smart waste management framework including the selection of a key use case of the most high-impact problem i.e., waste management, the data life-cycle and the use of mining techniques to deliver knowledge followed by a sustainable operation using machine learning to train and optimise the system architecture based on learning outcomes.

The smart waste transformation has been an emerging concept in the governance and administration whose fundamental models capturing the data lifecycles are still in early days of research. Since its early days, the key stakeholders such as researcher, industry practitioner, subject matter experts and users have associated with the topic from its applications perspective. There is limited knowledge available on fundamental building blocks and key catalysts involved in the journey of data to knowledge. After a methodical literature review of the resources available in the journals and over the web to understand the key facets of this topic, we have undertaken an exploratory qualitative study to identify this area of study requires further research. A high-level research in determining the field of study shows that data mining and machine learning can play an integral role in the development of smart waste management framework. It has proven challenging to orchestrate the architecture of a smart waste management with the dynamic nature of technology and functions.

We propose a smart waste management system consisting the following key components to provide effective and efficient waste management system. The framework of the proposed smart waste management system is show in Fig. 1

- Fill Level Indication: A fill level sensor must be installed in the bin which indicates the fill level information of the bin i.e., how much is a bin filled for example 25%, 50%, 75%, and 100%. These four levels are configured in such a way that they send notifications to the system administrator and the nearby vehicle through the GPS device fitted in the bin. We demonstrate a fill-level dashboard of our system in Section xx.
- Route Optimisation: As the real-time fill-level information is presented to the system administrator, it allows for the efficient planning of the route and provide optimised waste collection service. We provide a view of our Route Optimisation solution in Section xx.
- Number of Compression: A compression scissor being installed in the bin allowed to cut through the waste in a manner that it reduces the volumetric occupancy of the bin. For example if our bin allows 40L of waste then a compression scissors compacts the waste to be held in a small area freeing up rest of the space for more waste. This has a positive outcome on the fill-level meaning that the fill-level does not always increase but it can decrease as well after each compression cycle. While the fill-level notifications take place only when a certain threshold is reached. The compression cycle is run on-demand when the waste has increased the fill-level in an increment of 25%.
- Temperature & Humidity: This sensor provides information about the temperature of the bin to take any measure for reporting of a potential fire. Similarly, it reports on the humidity level of the bin as this will help determine the type of waste and allows the waste collection to classify the waste.
- Battery & Network Status: The battery and the GPS system fitted in the bin are powered by solar panels with a backup battery fully charged to ensure that the power is available for the cloudy days. If the backup battery has been consumed to the 50% then the system administrator are advised to schedule a maintenance activity to recharge the battery.

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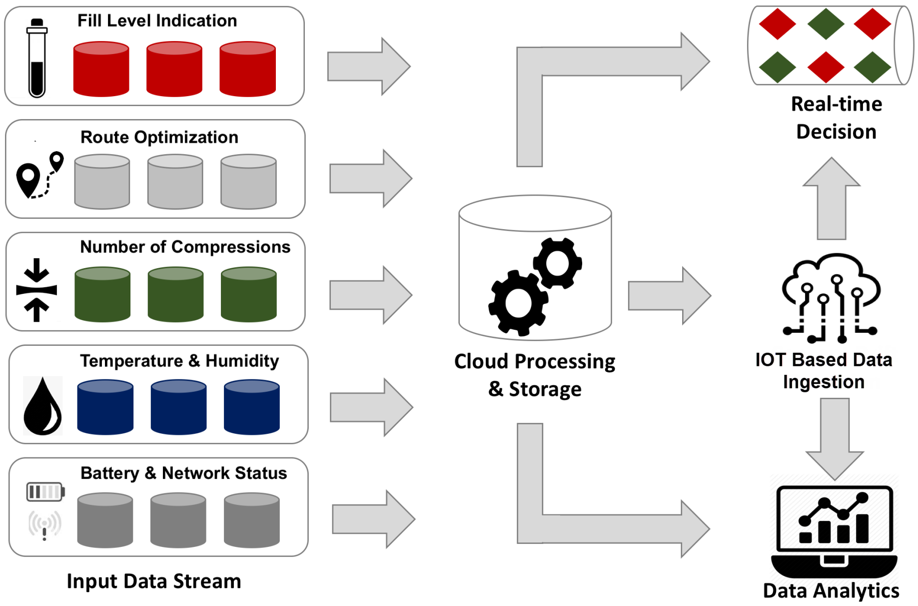

Fig. 1. Overview of Smart Waste Management.

1.2 Internet of Things for Smart Waste Management

To effectively manage a smart city, a large volume of data is collected using the IoT Internet of Things (IoT) such as sensors, actuators, and wearable devices capturing from the environment while cloud computing used to share data for processing, creating awareness and data-driven decision making [7]. However, the creation of these smart applications may come at a price of associated security and privacy problems due to the vulnerabilities which may exist in every layer of the architecture of a smart city application [1]. Another key problem is associated with the sharing of this data especially when the data is collected from multiple sources using crowd-sensing which is commonly used across IoT platform in smart cities and may soon outperform traditional methods of data collection which have seen reduction with the increase in the establishment of trusted relationships in smart city applications [8].

With the increasing number of nodes to collect the data from within the smart city, the applications collect a large volume of data from trasactional and consultative services. The information inferred from this data may inadvertently provide fluctuating patterns. This act of misinterpretation of data using techniques such as needs-based sensing and data analytics poses security threats on the decision being made using this data [9]. Moreover, it has been evident the usage of IoT and participation of citizens generates that a huge amount of data in smart waste management applications and services, deeming them essential for the success and timely improvement of the smart applications. Additionally, the storage and analysis of big data have been considered as an incredibly complex problem that requires a more modern-day solution as opposed to the traditional database systems. In order to mitigate, cloud solutions and big data technologies effectively manage large-scale data from various sources [10].

The overarching methods of smart waste management include using the IoT technology that aids in providing services in turn benefiting from the city-scale deployment of sensors, actuators, and smart objects. The primary driver for such services has been broadly classified as the stakeholders who are either the producers of data, the consumers of data or they are a combination of both [11]. Many researchers argue that Smart cities across the world are the next generation of urbanisation. However, this equally makes these cities challenging to run without violating and breaching the security and privacy of its citizens hence we propose the need within our framework to ensure that the data is secured. We harness the power of open platform using big data for the sake of visibility. A multifarious research yield in the IoT space has been focused on the use of data in a responsible way to yield meaningful results. The strength to which privacy and security are measures in a smart city is by keeping the data of the people living as anonymous and encrypted. These people have access to new electronic technology which is very different from traditional manual or mechanical equipment. Therefore, in order to ensure that the smart waste management remains smart, these electronic devices act as nodes that recognise different nodes of their own kind resulting in the ability to store and sharing data [12]. For smart waste management system we use the IoT devices by proposing a framework that provides a layer of abstraction and saves from the privacy and security concerns. We propose that the hardware for the smart waste management should be oblivious to the software of the system which will enable us to protect the data captured from the system. To effectively manage a smart city, a large volume of data is collected using the IoT Internet of Things such as sensors and actuators capturing from the environment while cloud computing used to share data for processing, creating awareness and data-driven decision making [7]. However, the creation of these smart applications may come at a price of associated security and privacy problems due to the vulnerabilities which may exist in every layer of the architecture of a smart city application [1]. Another key problem is associated with the sharing of this data especially when the data is collected from multiple sources using crowd-sensing which is commonly used across IoT platform in smart cities and may soon outperform traditional methods of data collection which have seen reduction with the increase in the establishment of trusted relationships in smart city applications [8].

With the increasing number of nodes to collect the data from within the smart city, the applications collect a large volume of data from transactional and consultative services. The information inferred from this data may inadvertently provide fluctuating patterns. This act of misinterpretation of data using techniques such as needs-based sensing and data analytics poses security threats on the decision being made using this data [9]. The purpose of this study is to establish and propose a smart waste management framework for smart cities using data mining and machine learning and shed light on how to address the key challenges empirically, theoretically and practically with a focus on both technical and functional avenues. The aim and objective of this approach is to propose a new dimension to the smart city modernisation and transformation landscape and look at it from various lenses including the data mining based modelling, technology centric architectures, business processes, digital execution and data-driven decision making. The motivation behind our product that was conceived as an IoT driven, connected, smart waste collection and management solution include the following.

– Categorise and organise waste in their dedicated compartments based on waste material such as green, recyclable, general, glass etc.
– Fill level sensors to monitor bin level.
– Near-to-real time reporting of fill level, temperature and other metrics.
– Smart dashboard to visualise data and trigger alerts, decision making mechanism.
– Enable the customer to utilise the bin surface for advertising (monetize), display information hence making it multipurpose bin.

There has been minimal research contribution in the field of smart city waste management framework in the context of smart cities using IoT's and algorithms of the Data Mining. It is a fairly new concept and it is very important to articulate the problem and suggest some answers to the common problems regarding smart city modelling faced by cities across the globe.

The structure of the remainder of the article is as follows: In Section 2, we provide an overview of our research by explaining the literature review process and the information collected so far. In Section 3, we introduce our proposed theoretical framework and system design. In Section 4, we define our research methodology, data collection process, and resource requirement. In Section 5, we evaluate our framework against the state-of-the-art evaluation criteria and performance evaluation metrics. In Section 6, we conclude our work and define the path for the next steps.

2 Literature Review

A systematic literature review has been done following several steps. The literature review has undergone various stages of deducing information from. Such structure has allowed us to focus on the most relevant papers that have been implemented during the literature review. We provide a summary of key findings in Section 2.2.

2.1 Identifying Research Questions:

The Internet of Things has been of paramount importance in the Smart Waste Management Framework for the collection of data and the interpretation

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of the underlying pattern. However, there are a number of sensors available from various brands that use myriad of back-end technology. Different sensors behave differently in different environment. To ensure that the overall smart waste management process is platform agnostic, there is a need for a framework to enable the smart waste management practitioners, city councils, municipalities, and researchers interested in the topic to work with the framework.

- Q1: How is the current market structured and the key features for the smart waste management in real-time in the Internet of Things?
- Q2: What are the existing competitors and the key characteristics of each of the system that have their differentiated propositions?
- Q3: How to best design a platform-agnostic framework for smart waste management that allows a level of abstraction in the architecture?

The search phrases during the literature review have been focused on the key concepts and technologies within the domain of Smart Waste Management and the Internet of things. A robust search strategy is used as an important step for extracting the accurate information related to the most important search strategies for manual search strategy and automated search strategy. A robust search strategy is used as an important step for extracting the accurate information related to the most important search strategies for manual search strategy and automated search strategy. This is clearly shown in the table 1 below.

Table 1. Search papers based on Key Concepts

Database	KC-1	KC-2	KC-3	KC-4	KC-5	Total
Google Scholar	1265	227	728	671	1721	4612
IEEE	1429	619	634	496	784	3962
Elseiver	1298	428	579	138	682	3125
Springer	1644	311	609	109	729	3402
ACM	1321	389	592	179	603	3084
Total	6757	1974	3142	1593	4519	18185

Where,

- KC-1 is Internet of Things in the Smart Cities
- KC-2 is Internet of Things in the Smart Waste Management
- KC-3 is Smart Fill-level detection
- KC-4 is Internet of Things Methods & Techniques
- KC-5 is IoT Architecture in Smart Waste Management

As it can be observed that thousands of papers have been retrieved for our research questions, therefore, it is important to use some sort of the Inclusion criteria and Exclusion criteria that will allow us to decide which papers are relevant in order to use as baseline for our research.

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2.2 Key Findings:

From the key relevant six themes presented in Fig. 2, we explain the systems proposed in each of the articles and discuss their attributes, which help us establish a baseline for our system.

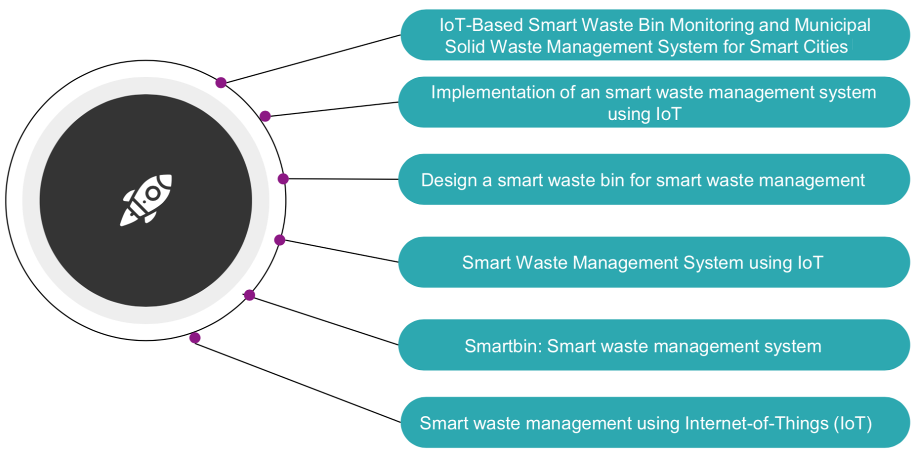

Fig. 2. Literature Review - Six Relevant Themes.

Due to unprecedented population growth and urbanisation, the increasing waste generation has become a significant challenge in developing countries.This has resulted in the management of the waste material to become a challenge. In one of the existing IoT-based smart waste bin monitoring and management for municipality has been proposed. This system helps to solve the problems associated with management of waste material. This system is capable of the management and collection of waste effectively, while detecting fire.

in waste material and forecasting of the future waste generation. The bins are electric in nature, and the IoT-based device performs the controlling and monitoring. These devices are wirelessly connected with the central hub to transmit the information about the filling level of the bins while informing of the existing location [13].

Since the cities today are rising at a sizeable rate, causing the waste collection to be exhaustive. One of the biggest challenges is the amount of trash of variety from general goods to metal. Most of the plans can handle waste once they are created, but it is not effectively managed. Another proposed system uses a mobile application associated with a Smart Trash Bin. The main aim is to reduce the personnel involved, and the efforts required for the enhancements of a smart city vision. This leads to the squashing of dustbins at regular intervals. The waste can be managed efficiently by implementing the smart bins on a large scale. The filling of dustbins can create a nuisance around promoting the unclean environment and may even lead to dreadful diseases [14].

As the smart bin is used to manage the waste on a smart city project. The system consists of sensors to measure the weight of waste and the fill level of the waste inside the bin. The system adapts with network environment, to manage information collected from waste management. In another article, a prototype of a smart waste bin has been proposed that is suitable for many kinds of conventional waste collection proposes [15].

As the population increases rapidly, there are sanitation issues related with respect to waste. This leads to unhygienic conditions for the citizens in the causing spread of infectious diseases. Consequently, the IoT based "Smart Waste Management" is used to manage the best solution. In another article, a proposed system is used for equipping the traditional bins with devices that will allow monitoring of their location and fill level of garbage in garbage bins. The data collected from the bins is used to manage garbage levels for optimised routing for garbage collecting vans, which will reduce the cost associated with fuel. The load sensors are used to increase the efficiency of data in relation to the management of garbage level and moisture sensors will be used to provide data of waste segregation in a dustbin. The analysis of data that is gathered will help the government to improve their plans. The system also helps generate reports for the smart waste management [16].

The smart bin system is used to identify fullness of the litter bin. It is designed to collect and deliver data through a wireless network. It helps employ the duty cycle technique. This reduces power consumption and maximizes operational time. The proposed system was tested in an outdoor environment. The data was collected and applied to sense-making methods. This helps in obtaining litter bin utilisation and daily seasonality data. This enables an increase in the productivity by providing data-drive decision making information to litter bin providers and contractors [17].

The smart cities are greener, safer, and more efficient using the Internet of Things (IoT). The quality of life is achieved by connecting devices, vehicles and infrastructure all around in a city. Various stakeholders work together to provide system integration, working with governments.Such solutions are built on an open, standards-based communications platform. In one of the state-of-the-art systems, a waste collection solution is presented using the IT prototype sensors. It can read, collect, and transmit huge volume of data over the Internet. Such data is processed by intelligent algorithms and used to dynamically manage waste collection. Simulations are carried out to investigate the benefits of such a system over a traditional system. Open Data from the city of Pune, India is used as the opportunities to innovate for Smart waste solutions [18].

The unique value proposition of the Smart Waste Management system usually include the fact that they provide a healthy environment by eliminating waste overflow, compressing more waste in less space, sending notifications to the stakeholders when the fill-level and temperature reaches a certain threshold, no maintenance required as the IoT sensors self-check their health and manages

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SOS. We compared our proposed product with the other three state-of-the-art Smart Waste Management system as shown in Fig. 3. These three systems have key features focusing on some sort of asset management and inventory for the trash bins in addition to monitoring using sensors. Additionally, some of these systems are managed using software applications. Furthermore, the systems are more hardware dependent, powered by solar, analytics platform, and on some occasions handling the fleet management.

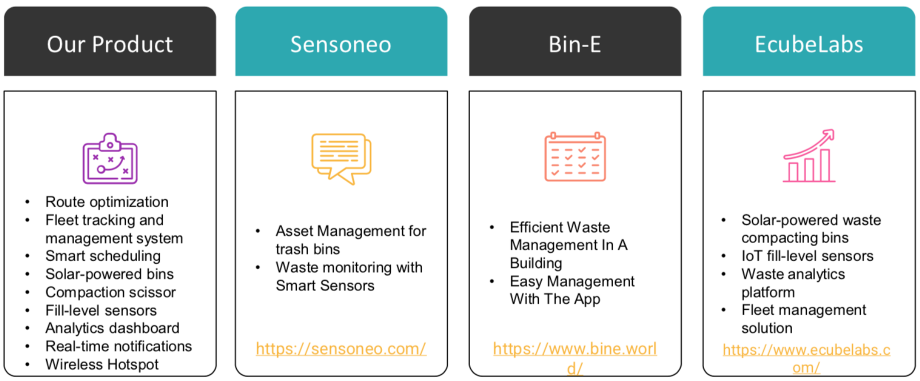

Fig. 3. Current Market Landscape.

Each of the framework in Fig. 4 demonstrate the key features of our proposed system against the other state-of-the-art systems. We use the features as the baseline to depict the comprehensive list of features. Each of the system is evaluated against those performance evaluation criteria. We demonstrate that our product has all the key features such as fill level sensor, solar-power, magnetic resistance so that the waste is not attracted, some way of sorting the waste, compressing the waste, offering GPS based location sharing so that the fleet management can be effectively routed, providing real-time notifications, offering wireless hotspot, and offering reporting and dashboard. However, since the topic of our discussion is the creation of a level of abstraction hence, we do not need to rely on one vendor or another to provide these features. We provide an empirical evidence of why our system can perform with sustainability without depending on a particular hardware architecture. We study the pros and cons of the current market in light of the smart sensors from within the smart city, open sources of data, use of the analytics platform for the extraction of knowledge, and converting them into actionable insights, route optimisation, and smart scheduling of the waste collection, privacy and security of the data that is collected from the environment along with inter-department data sharing, and real-time notifications along with the provision of hot spot.

The pros of the current market competitors as shown in Fig. 5, mainly lie in using the smart sensor for the collection of data, while offering open source

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Features	Our Product	Sensoneo	Bin-E	EcubeLabs
1. Fill level sensor	✓	✓	✓	✓
2. Solar-powered bin	✓	✗	✓	✓
3. Magnetic resistance	✓	✓	✗	✗
4. Asset Management	✓	✓	✓	✗
5. Sorting of Waste	✓	✗	✓	✓
6. Compression of Waste	✓	✗	✓	✓
7. GPS based Location Sharing	✓	✓	✓	✓
8. Route Optimization	✓	✓	✓	✓
9. Real-time Notifications	✓	✗	✗	✗
10. Reporting & Dashboard	✓	✓	✗	✓
11. Wireless Hotspot	✓	✗	✗	✓

Fig. 4. Comparative Analysis.

data for the data sharing and learning purposes. Finally, the analytics platform is used for extraction of underlying patterns, training of the system on this knowledge so that the learner models are updated for future. Whereas, the cons are mainly in the hardware space where there is lack of route optimisation due to the limited information available from the bins, similarly the scheduling of the waste collection requires efficient algorithms that timely report and overlay that information on geo-coordinates. The use of privacy and security protected data collection is of essence to ensure that no element of citizen security is compromised. Finally, the real-notifications that are triggered when an event takes place is another key feature that is lacking in current systems.

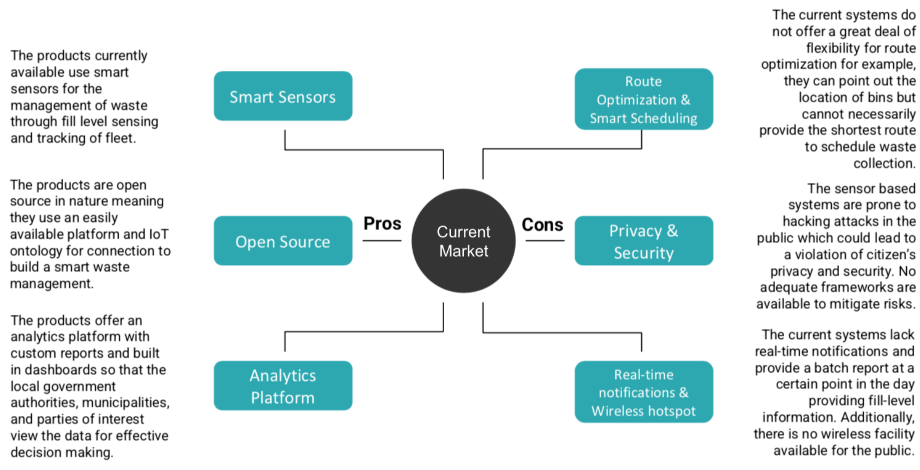

Fig. 5. Pros & Cons of the current products.

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3 The Proposed Platform Agnostic Framework

The research on the Smart Waste Management Framework has been designed in such a way that it has been categorised as follows:

– Approach: The literature review has been used to shortlist the key functional areas of the research on the subject knowledge and in order to develop the relationship between the technology stack and the functional value that the framework brings to the Smart Waste Management.
– Method: The research has used a digital lab to build a sensor network using fill-level sensors and collected data from real scenarios and have also simulated data. Furthermore, the literature review has been carried out using the state-of-the-art articles and reputed databases. Additionally, a desktop evaluation of various tools have also been carried out along with the hands-on use of hardware and software to experiment and develop a a platform-agnostic framework.
– Requirements: The access to the reputed journal databases will be required, in addition, to various testing platforms such as different OS loaded mobile phones, tablets, laptops and desktops will be required. Furthermore, the access to the on premise and cloud infrastructure will be required.

Furthermore, our system provides a soft edge technology that allows hardware to become just soft nodes from which data can be ingested and the remaining operations are carried out on the software layer. Similarly, we make our architecture independent of the middle ware that allows the system to offer all of the hardware features as well. For example, we offer smart route planning, help achieve operational efficiencies, and cost reduction by reducing the waste collection frequencies, offering a transparent process by tracking and dashboard facilities. Additionally, we allow our stakeholders to make data-driven decisions by timely providing the alerts and notifications. Such an implementation helps reduce a carbon emission and help maintain a clean environment.

Here we highlight some of the key advantages of our product that focus on two key aspects in relation to the system i.e., the hardware and the software. The level of abstraction that is offered by our framework focuses on allowing our system to use all of the hardware functionality yet without relying on a particular type of hardware. Similarly, our framework delivers on multiple outcomes i.e., it is platform-agnostic meaning any hardware can work with our system and deliver the same outcomes.

3.1 Hardware - Outside – Top of the bin

The outer section of the the smart bin is built using high-grade stainless-steel galvanised body with powder coded and painted with Teflon. A solar panel with poly carbonate shield is placed on the top of the smart bin.

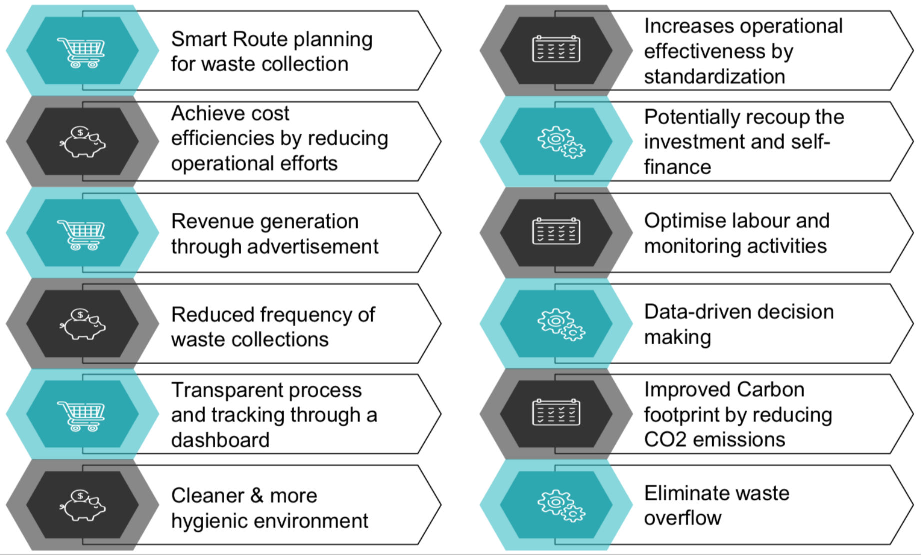

Fig. 6. Proposed platform agnostic smart waste management framework.

3.2 Hardware - Inside – Top of the bin

- Scissor compactor (8X) with shutter lock mechanism when the citizen is trying to throw the waste in the bin.
- Fill-level sensor at least 25%, 50%, 75% and 100% with LED colours representing the fill-level of the bin on the body of the bin.
- Thermometer/ Temperature sensor to capture the temperature of the bin. The bin's maximum allowable temperature is 80 C and -30 C.
- Relay operated electric lock to open the bin from the top – two locks operated; one during the compression lock the bin and use the same with different command for the waste vehicle person to open the system – show whether the bin is locked or not.
- Battery support at least 24 hrs with anti-theft protection.
- Wireless connectivity, GSM/ GPRS support.

3.3 Hardware - Front of the bin

- The bin must have openings for the citizens to throw waste inside the bin.
- LCD Advertisement screen on the front sides.
- Buzzer should be sounded if the fire is caught inside the bin and open fire extinguisher water inside the bin.

3.4 Hardware - Sides of the bin

- LCD Advertisement screen on both right and the left sides.
- Steel based ashtray on both the sides of the bin.
- Spray the fragrance outside the bin.

3.5 Hardware - Back of the bin

- AC Power plugin – Hybrid.

3.6 Hardware - Bottom of the bin

- A tray to drain water present in the waste inside the bin.

3.7 Software - Admin Panel

- Centralised dashboard of the bins on a map with their details as a pop-up box such as a particular bin's location, temperature, fill-level, battery status and fire extinguisher.
- From command centre, send SMS or in-app notification to the waste collection vehicle.
- Show the location of the bin on a map – overlay map with bins.
- Show whether the bin is locked or not – if the bin is not locked then send notification to the waste vehicle driver.
- Show fill-level status of bin on the dashboard and notify the waste vehicle driver on their app – send notification to the nearest waste collection app drive along with the location.
- Show the temperature inside the bin – if the temperature of the bin has been high for over 3 minutes and even the fire extinguisher did not put off the fire within three minutes then send notification to the nearest waste vehicle driver.
- Show fire extinguisher status in the bin and notify if the percentage is low.
- Show the percentage of battery is charged and charging status (whether battery is charging).
- On the dashboard, also show that the last time bin was emptied, who emptied it and how many times a bin has been emptied in the month/ year, collection efficiency i.e., number of visits last year vs this year etc.
- Show reports with date ranges and search functionality.

3.8 Waste Collection Vehicle App

- Receive notifications from the admin panel on the following occasions.
  - Map with Bins in proximity with their fill level information, geocoordinates and physical address, their temperature, fire extinguisher and batter status.
  - When the fill-level of the bin is 75% and above.
  - When the temperature of the bin is over 80 °C and under -30 °C.
  - When the fire extinguisher is low on the extinguishing gas.
  - When the battery of the bin is lower than 50%.
- Communicate with the admin panel command centre via SMS and telephony.
- Capture image and post on the admin panel repository.
- Fill a questionnaire on efficiency of collection.

4 Data collection

For the Artefact Development approach, we have used three types of datasets including the one from one of the smart cities in Australia, and two of Google datasets. We explain these datasets below. In addition to the real datasets, we have also used synthetic datasets in order to evaluate the performance of our framework. The following is the process that will followed in the collection of data:

- The primary data will be collected from the desktop evaluation of the case studies available in research journals and industry resources & publications.
- The secondary source of data is through discussion and consultations with the industry best practices. The line of questioning will be collated using the facts gathered from the primary data source and require validation from the Smart City best practices available on the web.
- The third source of data is through the experiments performed using existing tools and framework using Predictive Analytics techniques, and Machine Learning algorithms. These tools will be available on the internet or from the Smart Cities that are under study.

4.1 Data Pre-processing & Data cleansing

In the data pre-processing and data cleansing stage of the process. The following is the process that will followed in the analysis of data collected in the process above:

- The analysis of data collected from the interviews, surveys and the experiment using Fog and Edge technology, interpreted via Data Mining algorithms, and Predictive Analytics techniques to extract actionable insights and Machine Learning to train and supervise the systems, will be performed in such a manner that all the findings are coded to help define recurring themes. These themes can further be analyzed using big data tools to determine a data pattern.
- The data pattern generated from the data collected will then allow mapping the gap between the theoretical framework and the experimental results. It is important to map this gap in order to assess the suitability of the Smart Waste Management Framework using the hybrid multi-cloud architecture in a smart city to the real-world business challenges.
- Finally, the data collected that has been collected, the pattern extraction and the causal relations between various entities in the data has been identified between the parameters for the Smart Waste Management which is then established in the workings to be used to validate the bases of a platform-agnostic architecture for a Smart Waste Management framework.

4.2 Data Sampling

In data sampling, the data in the dataset has been splitted into 30% for testing, that means, 70% of data will be allocated for training purposes and 30% will

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be allocated for the testing purposes. To be precises, 70% percentage of data has been allocated for training and 30% percentage of data has been allocated for testing purposes. The framework assessment and validation are important parts of supervised machine learning. When evaluating an model's prediction performance, it is critical that the method be unbiased. The user of the day may split a dataset into subsets using train test split() from the data science toolkit scikit-learn to reduce the possibility of bias in the assessment and validation process. Before calculating the prediction accuracy, the dataset must be split into two or more subsets.

As a general rule, it's usually adequate to divide your dataset into three equal subgroups. Training the model to given data is done by applying the training set to it. The evaluation of the model in an unbiased way is carried out during hyperparameter adjustment using the validation set. In order to get the model set-up for each hyperparameter setting examined, one first train the model using the training set and then conduct an assessment on the validation set. In order to develop a completely impartial model to test the final framework, we intend to use a test set which is required.

4.3 Performance Evaluation

We use a number of performance evaluation criteria in order to evaluate our framework for the reporting of the predictive forecasting of the smart waste management system.

The waste fill level prediction performance metrics focus on the performance of a waste fill level predictor. We divide this into four significant areas in the order of the impact they have on the classifier: (i) Rate of false positive (Type-I error), (ii) Rate of false negative (Type-II error), (iii) Predictive delay, and (iv) Predictive accuracy.

1. The rate of false positive of a predictor framework incorrectly raises an alarm that the fill-level has been detected when actually there is no fill-level occurring in the underlying data. A high false positive rate may impact the classification accuracy depending upon the model adaptation strategy in place for example, a false positive may unnecessarily cause a decision tree to reset itself leading to a reduction in the classification accuracy. Similarly, noise and outliers may also adversely impact classification if not controlled properly.
2. The rate of false negative of a fill-leve detector inaccurately misses a fill-leve when actually there exists one. Due to the existence of false negative, a fill-level predictor misses an opportunity to identify fill-leve and consequently alarm the classifier of the change in the underlying distribution. The impact of false negative is that the classifier continues to use the model it had previously been trained on.
3. A predictive delay represents an estimate of change detected and is commonly represented in terms of timestamps or the number of data records

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required to predict a fill-level after the change has actually occurred in the underlying distribution.

4. Predictive accuracy represents the accuracy of our framework based on how effectively it predicts fill-level. It benchmarks its performance against the confusion matrix analysing the rate of false positives, false negatives, true positives and true negatives. This also helps benchmark how well our framework is capable of predicting fill-level when combined with any predictive analytics technique.

The following equations represent how the above discussed parameters aid in measuring the performance of our framework. We aim to analyse these parameters to benchmark the performance of our algorithms.

Parameter # 1: Sensitivity also known as Recall, can be expressed as:

$$Sensitivity(\beta) = \frac{Number\ of\ TP}{Number\ of\ TP + Number\ of\ FN} \tag{1}$$

Parameter # 2: Specificity can be expressed as:

$$Specificity(\chi) = \frac{Number\ of\ TN}{Number\ of\ TN + Number\ of\ FP} \tag{2}$$

Parameter # 3: Positive Predictive Value also known as Precision, can be expressed as:

$$PPV(\rho) = \frac{Number\ of\ TP}{Number\ of\ TP + Number\ of\ FP} \tag{3}$$

Parameter # 4: Negative Predictive Value can be defined as:

$$NPV(\upsilon) = \frac{Number\ of\ TN}{Number\ of\ TN + Number\ of\ FN} \tag{4}$$

Parameter # 5: Rate of False Positives can be defined as:

$$FPRate(\theta) = 1 - \chi \tag{5}$$

Parameter # 6: Rate of False Negatives can be defined as:

$$FNRate(\pi) = 1 - \beta \tag{6}$$

Parameter # 7: Accuracy can be defined as:

$$Accuracy = \frac{Number\,of\,TP + Number\,of\,TN}{Number\,of\,TP + Number\,of\,TN + Number\,of\,FP + Number\,of\,FN} \tag{7}$$

where, TP = True Positive, FP = False Positive, TN = True Negative, FN = False Negative.

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5 Multi Agent Deep Re-enforcement Learning

Figure 7 depicts the proposed system framework for performing smart waste management using IoT sensors. The framework presented here provides an overview of the working structure at each bin. Each agent in the proposed system framework will be assigned to each bin to actively monitor its status. Each agent associated with a bin will attempt to learn its own policy by taking appropriate actions to optimise its own reward function. At each time step t, the agent observes the environment state S, decides on an action A, receives a reward R_{t+1}, and finds itself in a new state S_{t+1}. The agent obtains information about the

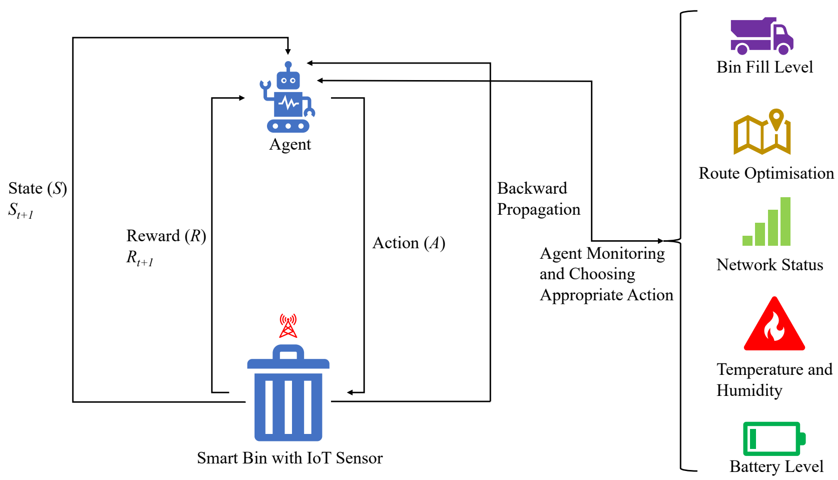

Fig. 7. Overall proposed system framework of smart waste management through IoT sensor enabled multi-agent deep reinforcement learning.

bin's state S via smart IoT sensors connected to each bin. To actively monitor and use the information to take appropriate action A, the state S contains the real-time bin fill level, temperature, humidity, battery, and network status. Based on the bin status, the information will be used to train the model and trigger the system to take appropriate action A. The agent will be rewarded R based on the action A taken by the agent. The system will monitor the bin fill levels and also learn the bin filling patterns to schedule an optimised route planning for trash collection. Pattern analysis of bin filling will decrease the chance of triggering compression button and to avoid overfilling of the bin.

In the system framework, backward propagation is used to fine-tune the weights of the neural network based on the loss function (difference between actual and predicted value) at each epoch (iteration/training episode). The tuning of network weights reduces error rates and increases model reliability. Tuning is accomplished by calculating the loss at each node in the neural network. The penalty in the reward function will be applied based on the loss function by giving it a lower weight value. Fine tuning optimisation aids in improving model significance and yielding smaller losses in the next epoch.

6 Conclusion and Future work

Waste management within the growing metropolitan cities has been a long term concern. With the passage of time as the cities move toward urbanisation and with the increase in population and the consumption of industrialised goods, waste management has been a concern of paramount importance. In order to resolve this issue, development of a smart waste management system will aid the cities to manage their wastes both efficiently and effectively. These systems contain a hardware and a software component which are often so closely knitted that it becomes hard for one to function without another. Through our research we propose a platform-agnostic framework for the management of the waste within smart cities. Our platform uses several layers of abstraction and provide the access to the underlying architecture through as-a-service model. We use the IoT devices for the collection of data and then ingest this data in our data management pipeline which further breaks down the data into three component for the best utilisation including notifications, report building and predictive analytics. Through empirical evaluation we achieved our preliminary results that highlight that we have a high recall, and precision with a high prediction accuracy, low prediction delay. These results motivate us to pursue further work and extend this research to implement a range of APIs (Application Program Interface), and open data framework for the easy of data sharing within privacy protected smart cities. The future work of this research mainly focuses on the development of a service based architecture where a number of APIs are built and made available for the other smart city services to use. Additionally, we intend to provide the privacy and security protected data sharing standards for open data sharing and governance within the smart city portfolio applications.

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