Data Driven Waste Management in Smart Cities

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Abstract

Waste management is a critical issue worldwide. One of the major challenges in waste management is the efficient collection and transportation of waste from the source to the disposal facility. Research shows that systematic adoption of data-driven technologies (e.g. Machine Learning and Internet-of-Things) can assist public utilities (Kommune) by a) improving the waste collection management process, and b) minimizing the total incurred cost (Misra et al., 2018; Komninos, 2007). Thus, in this work, we show that systematic adoption of data-driven techniques can significantly improve the waste collection process and minimize the incurred cost to public utilities. In order to perform experiments, we generate a synthetic dataset motivated by a real-life urban environment. Also, we aim to present different approaches to cost-benefit analysis in the targeted scenario. Our study shows that the systematic use of Internet-of-Things-based smart garbage bins, smart transportation algorithms, and Machine Learning can significantly reduce the total incurred cost of public utilities operating in this space.

Keywords – Internet of Things (IoT), Machine Learning, Smart City, Smart Garbage Bins, Effective logistic management

Contents

Abbreviations

AI Artificial intelligence

ICT Information and communication technology

IoT Internet of Things

ML Machine learning

NFC Near field communication

SCC Smart connected communities

SDG Sustainable development goals

1 Introduction

1.1 Academic background for the study

Globally, the implications of extensive industrialization and exponential growth in population lead to a substantial increase in the amount of waste being produced. Therefore, efficient and effective waste management and its long-term sustainability are now an increasing concern around the world. Waste management encompasses each and every step that goes into managing waste, from its production to its ultimate disposal. The waste management industry has different functional groups based on the collection, dumping, segregation, recycling, and waste prevention to mitigate the adverse impacts of waste pollution on the environment. According to a world bank report (World Bank, nd), 2.01 billion tonnes of municipal waste are produced globally each year, with at least 33% not being handled in an environmentally sustainable way. With waste creation predicted to exceed 3.40 billion tonnes by 2050, this issue is only expected to become worse as shown in fig. 1.1.

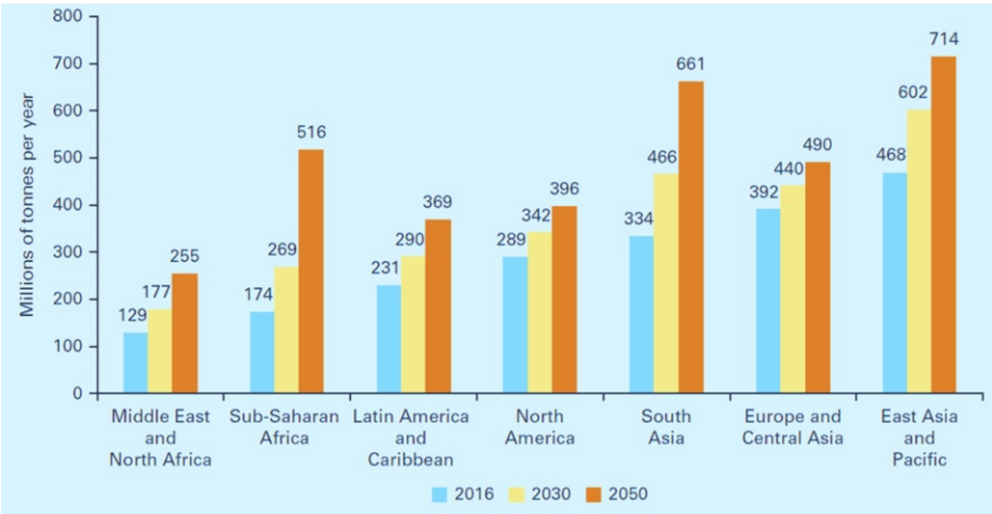


Figure 1.1: Estimated Waste Generation (World Bank, nd)

With the advancement in technology, municipalities (Kommune) can leverage Internet-of-Things (IoT) and Machine Learning (ML) to address these challenges. As demonstrated by its widespread use in modern supply chains, IoT management systems have proven to be valuable in optimizing and automating processes in the waste management industry, whereas, ML has been successful in the development of state-of-the-art prediction algorithms. In this work, We aim to explore a) how the smart use of IoT and ML can assist public utilities in order to manage the problem of garbage collection and b) how to minimize the overall incurred cost. To achieve this objective, we constructed some scenarios as part of our thesis research - which is motivated by real-life examples. However, first, we would like to explain our understanding of IoT/ML and provide a basic reflection on them.

First, we present our reflections on IoT. Though there is no generally agreed definition of IoT, however, in general, IoT can be defined as:

"The Internet of things (IoT) is the inter-networking of physical electronic communication devices which are embedded with electronics, software, sensors, actuators, and network connectivity which enable these objects to collect and exchange data" (Kiran, 2019).

The basic essence here is to make regular objects and devices compatible with the internet by communicating both with the users and other objects. Many of these technologies also go under the broad term ICT. Furthermore, the significance of using IoT can be explained by the fact that it can help to reduce costs and improve efficiency through different processes being automated. This will help the companies as well as municipalities to make data-driven decisions. IoTs significance today is very high and relevant because it is transforming many traditional processes related to smart cities. Moreover, Jadli and Hain (2020) mentions that artificial intelligence is also another important uptrending technology that when applied can see patterns for example of waste production. This can provide different benefits compared to just using sensor technology without analyzing it.

The chronology of employing the Internet of Things (IoT) encompasses the phases of procurement, deployment, and maintenance. Given the swift pace of technological progress, IoT presents a promising instrumentality for effectuating mitigating measures in waste management. This is done by binding different technologies together and turning traditional services into more efficient, smarter, and sustainable paths (Mohanty et al., 2016). This is what transforms regular cities into smart cities by using the huge amount of data that is generated in an efficient, systematic, and sustainable way with the help of integrations that are connected together. Smart cities can be seen as a system of information and flow that can be optimized, controlled, and modified to achieve goals in different segments (Grossi et al., 2020). IoT is essentially the main part of it. "Efficient waste collection is a fundamental service in smart cities" (Medvedev et al., 2015). We have gone into more detail about the smart bins. In fig. 1.2, we show the conceived structure of how smart bin can look like:

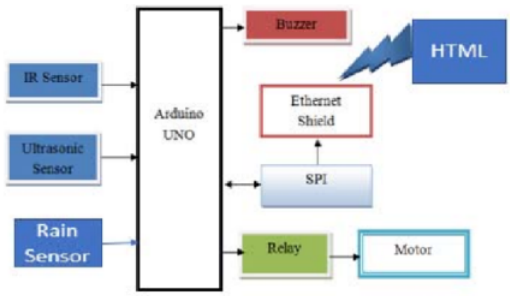


Figure 1.2: Example on how a smart bin can look like with parts (Murugaanandam et al., 2018)

This has further led us to take on comparative analysis in this thesis. In recent years technology upgrades within the telecom/networking sector have occurred such as 5G. This type of technology is faster and more compatible with bigger amounts of data. The development of smart cities is a crucial focus for IoT development, as it encompasses various challenges, including managing traffic flow, improving air quality, providing solutions for public safety, optimizing parking, implementing intelligent lighting systems, and facilitating efficient waste collection (Kumar et al., 2019).

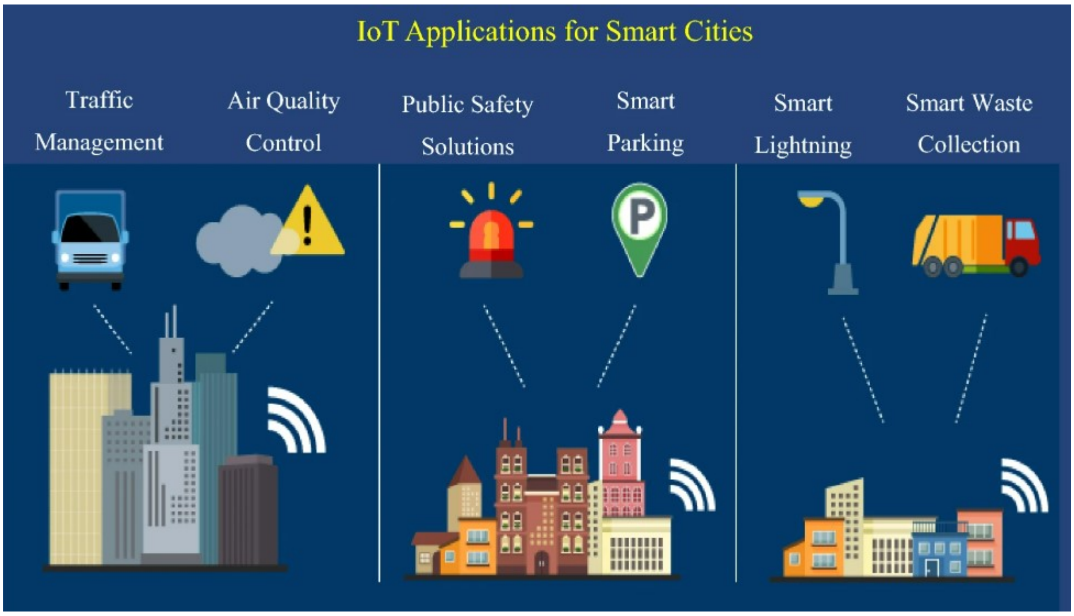


Figure 1.3: IoT applications for Smart Cities(Kumar et al., 2019)

The increasing utilization of IoT, smart gadgets, sensors, and machine-to-machine communication in a smart city has the potential to decrease expenses due to inefficiencies in garbage collection procedures (Anand, 2021). When it comes to using IoT technology in waste management, there are numerous different scenarios to select from.

The efficiency of waste collection can be increased with the use of new waste management technology like smart bins. These innovative tools would allow waste management companies to collect different types of information about the smart bins such as weight, capacity, location, temperature, and fill level. With this information, garbage collectors would be able to effectively address immediate waste disposal needs. Moreover, IoT solutions can assist drivers in determining the most efficient and fastest routes to optimize their waste collection efforts. This approach is not only systematic, but also guarantees the smooth operation of pickups.

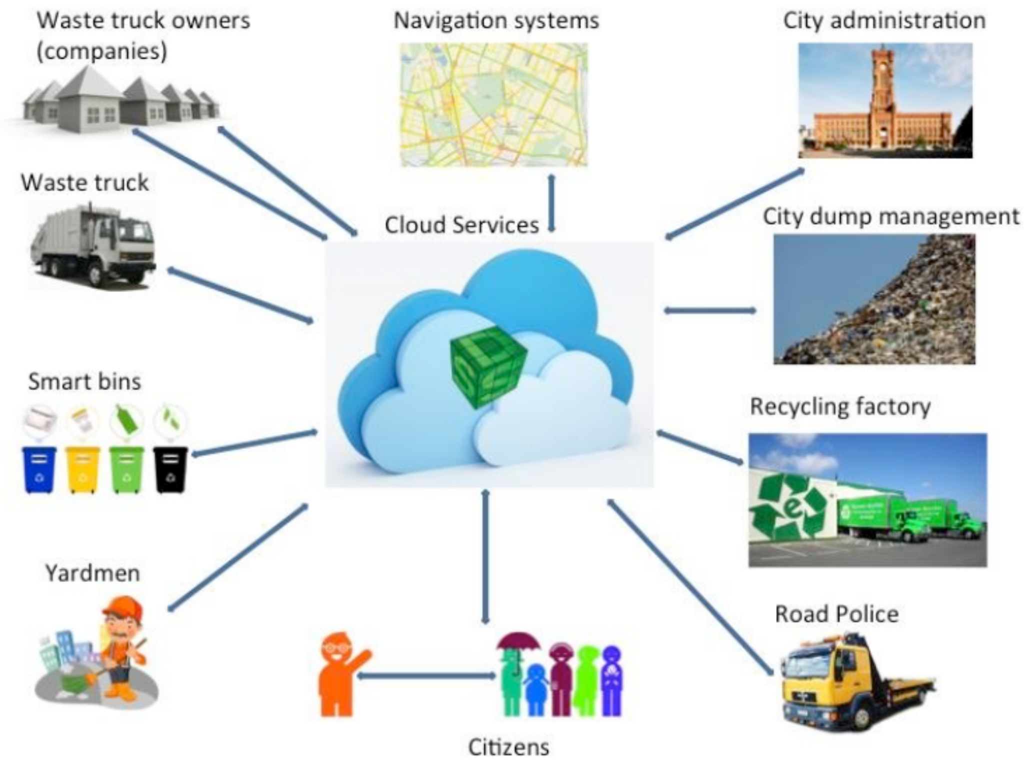


Figure 1.4: A framework of IoT in waste management (Medvedev et al., 2015)

It is hard to provide an exact number of countries that use IoT in their waste management and to which degree. Smart cities do exist to an extent, however, the utilization of smart waste management systems is still not common. According to (Sensoneo, nd) they have customers in more than 80 countries with different projects to contribute to smart waste management. Several countries have launched different kinds of prototypes. For example, Singapore has launched a pilot project on a smart bin called BINgo which will be placed in three locations for one year approximately (Ocampo, 2022).

These smart bins are using a combined technology of AI and IoT such as smart sensors (Ocampo, 2022). It is getting more popular to look for smart solutions that will make traditional methods outdated. The Singapore smart bins and Sensoneo aim to achieve various benefits through their respective initiatives. The former seeks to elevate recycling rates, while the latter adopts diverse methods, predominantly leveraging data-driven solutions, to address the waste issue. This has several benefits such as reduction of waste costs, time savings, and collection costs for the different projects at (Sensoneo, nd) depending on which smart waste solution has been applied.

Waste management system of the target city

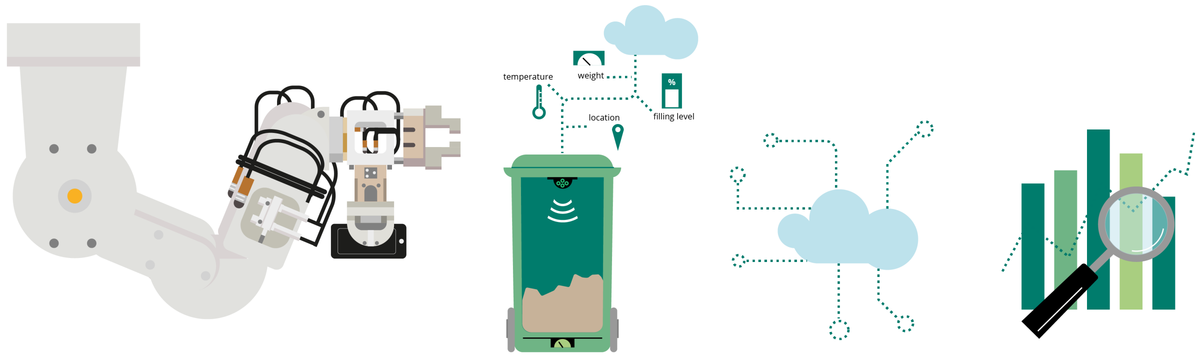
Skedsmo was a municipality in Akershus county, Norway. They were then merged into Lillestrøm municipality together with Fet and Sørum in January 2020 (Lillestrøm kommune, nd). The waste management system of Skedsmo is controlled by the municipality's public services. They are responsible for overseeing recycling and waste reduction efforts. The public service ROAF Lillestrøm are responsible for collecting and disposing of municipal waste in Skedsmo and operating the landfill. The main issues that we are looking for are quite common to any other municipality. We assume that this issue also applies to Skedsmo. This is related to reducing waste generation, increasing recycling and composting, and improving the efficiency of waste collection and transportation.

By introducing IoT (Internet of Things) technology in the waste management system of Skedsmo will in return give several advantages. IoT can help optimize the waste collection process by providing real-time data on waste levels in bins and containers. This data can be used to plan more efficient collection routes and schedules, thereby reducing the number of collection trips and associated emissions.

1.2 Motivation

Considering technology's universal impact on various aspects today, it becomes important to find out new ways that may facilitate a shift toward sustainability. The motivation for this thesis comes from the pressing issue of climate change and its substantial implications on the welfare of the world's population. Knowing its potential to disrupt the quality of life of a large population around the world, it is essential to find a solution that may help in implementing an improved waste management process. Conventional waste management techniques are inadequate in managing the escalating quantities of waste being generated.

Furthermore, poor waste management practices can result in adverse environmental consequences and subsequent side effects on the environment. In response to such outcomes, environmental activists are calling for proactive measures to curb pollution and avert further environmental degradation. A notable example is Greta Thunberg, a renowned Swedish youth activist who has spearheaded global environmental campaigns to mitigate the impacts of climate change (Garvik and Tjernshaugen, nd). Such activists have motivated us to look for solutions that can be effective and reduce the climate impact.



	Robotics	Artificial intelligence and neural networks	Internet of things	Cloud computing	Data analytics
PROCESS	Advancements in the pneumatic sorting process as a result of automation technology allow producing defined waste streams of high purity (over 90 %).	Machine learning — using neural networks based on the use of data or examples to solve problems without explicit programming — is used for classification and pattern recognition in the waste management context, improving the efficiency of sorting.	As more and more devices are connected to the internet or other networks, sensor-supported containers can collect data and transfer it to central units.	Storing and processing of sensor data and cloud based software solutions make it easy to optimise workflows and document failure to collect, failure in sorting or detect waste bins that are not paid for.	Processing and analysing data plays an important role in the recycling industry in order to identify patterns, extract information, discover trends or calibrate models. This knowledge is important in order to evaluate different options for the transition to a recycling economy.
EXAMPLES	- Robots that are able to identify and sort recyclables and critical materials through image recognition/IR scanning/AI vision systems when dismantling used phones/electronics	- Autonomous, self-driving street sweepers, refuse trucks	- Smart waste bins with identification systems, weighing systems, level sensors, temperature sensors, sofware for optimising logistics	Cloud based software for: - Connection, standardising and optimising internal procedures - Real-time order management, route planning and optimisation, customer self-service, order-tracking and evaluation	- Electronically supported diposition of waste collection vehicles - Evaluation of sensor data for automated sorting plants - Control of waste incineration plants - Drone based data collection on landfills

Figure 1.5: Overview IoT applications from European environment agency (EEA, 2021)

Sustainable development goals (SDG) are also something that has motivated us from the UN. According to the (United Nations, nd) goal 11 is making cities and human settlements inclusive, safe, resilient, and sustainable.

The imperative of sustainability is a paramount concern for both individuals and entities, with achieving a balance between cost and sustainability being pivotal to catalyzing action among contemporary companies and municipalities. In this context, cities must adopt an effective and data-driven approach to decision-making, and deploy relevant technological innovations that enhance efficiency and promote sustainable practices.

Thus, we decided to touch on the aforementioned issues in the master's thesis. We believe that data-driven garbage management can potentially improve the garbage collection process, and at the same time, will address the challenges of UN SDG.

1.3 Objective and research questions

This thesis is inspired by the model of Misra et al. (2018) that focused on optimizing routes of the garbage collection process with the help of IoT, and which will serve as a baseline for our research. Our main objective is to explore and research the capabilities as well as potentials of IoT technology in regard to waste management cost reduction. Hence, we are looking forward to studying how IoT technology may improve conventional waste management techniques as well as increase their efficiency and sustainability. We basically aim to provide new perspectives and insights into the use of technology for promoting sustainable waste management practices as shown in fig. 1.6. For our research, we will create a hypothetical scenario to simulate and evaluate the effectiveness of IoT-based waste management. In addition to that, we will cover how smart algorithms and Machine learning can be useful in order to efficiently manage the collection of garbage in an area of interest.

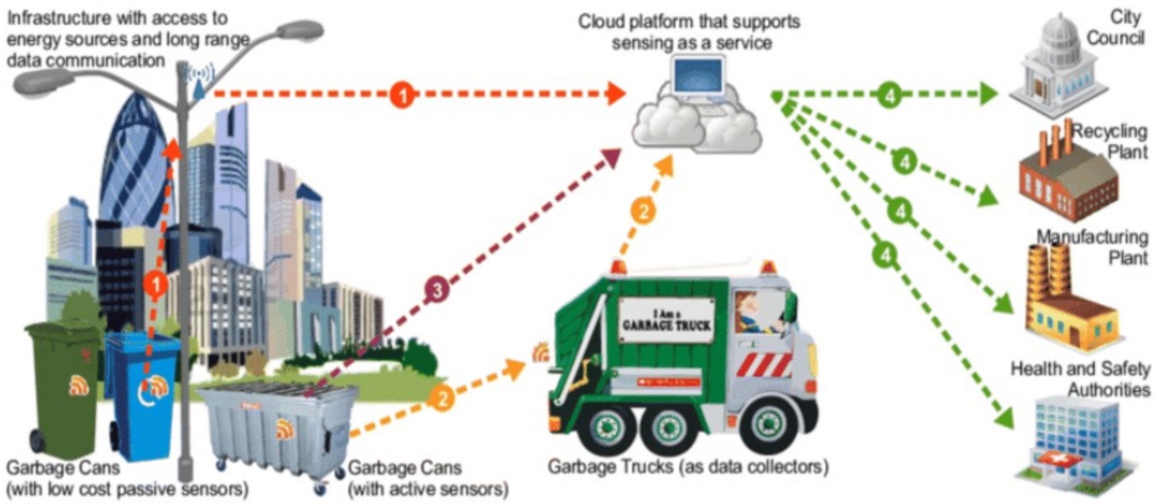


Figure 1.6: Possible ways to collect data and store it on cloud platform services and share info with different departments (Alqahtani et al., 2020)

Our framework for this thesis will aim to focus on three research questions that we believe are relevant to the waste management problem.

Research Question 1: We will focus on the analysis of the impact of IoT on waste management. We will formulate a methodology of analysis. This research question will demonstrate that how public utilities can improve their garbage collection process via IoT.

Research Question 2: We will aim to develop a comprehensive and thorough approach for conducting a cost-benefit analysis of IoT- Waste Management solution. The main aim will be to formulate a mathematical approach, which will assist us in the analysis. The analysis aims to provide valuable insights regarding the financial impact of IoT technology in the context of waste management. Moreover, we will cover smart algorithms from literature which can potentially minimize the incurred cost furthermore.

Research Question 3: We will cover how ML can be used in order to predict garbage. In other words, how ML can provide prior information to public utilities in order to better plan the resources. We show a prediction algorithm using Deep Learning.

1.4 Thesis outline

The thesis will begin with an introduction that sets the context and presents the problem statement, research questions, objectives, and significance of the study. The scope and limitations of the study will also be outlined. The second chapter will be a comprehensive literature review covering the related papers published about IoT, waste management, and the role of IoT in creating smart cities. The third chapter will present an overview of the available IoT technologies in the market, particularly those related to waste management.

The fourth chapter will draft and explain the methodology used.

in this study which will explain in detail information on the research design, the data collection and analysis, hypothetical scenarios, and a cost-benefit analysis. The study is aiming to provide a deep analysis of IoT-based Waste Management systems by following the mentioned methodology. The fifth chapter will focus on showing the results of our studies, motivated by real-life scenarios.

The discussion and conclusion section will present the findings of the study, their implications, and any limitations. We will conclude this thesis by providing future research directions.

2 Related work

Effective management of waste represents a critical issue in the context of smart cities. This is where an increasing urban population generates a remarkable volume of waste. The utilization of Internet of Things (IoT) technology has demonstrated the potential to ameliorate waste management efficiency and curtail costs. Specifically, a noteworthy instance of IoT application in waste management is the deployment of smart bins, which can monitor waste levels, optimize collection routes, and encourage recycling.

The underlying idea of such a sensor-based system is to capture the status of the waste bins in real time, which are spread across diverse locations. Once, the waste bins are near the status of being filled; the waste collections trucks collect the garbage and empty the waste bins. This approach can significantly reduce the overall cost of the waste collection process. With the advancements in the sensor development of telecommunication technologies, Internet-of-things have become an important paradigm. According to Mohanty et al. (2016), the IoT is the foundation of the impending generation of smart cities. The sustainability of the smart city can be improved by increasing operational efficiency by lowering operating costs.

Several researchers have proposed IoT-based smart systems to address issues with waste management in smart cities. These proposals have come from researchers including (Jin et al., 2014; Sun et al., 2016; Montori et al., 2018). A framework for developing smart cities utilizing IoT technologies was provided by Jin et al. (2014), where the significant emphasis was put on waste management. According to Sun et al. (2016), the Internet of Things (IoT) has the potential to create a widespread network of smart sensors and connected devices for Smart and Connected Communities (SCC), and big data analytics has the ability to make it possible to transition from the IoT to the real-time control that SCC desires. Montori et al. (2018) devised an architecture called SenSquare (based on Collaborative IoT), in order to give consumers uniform access to heterogeneous data sources from open IoT platforms and crowdsensing initiatives.

The use of ICTs for SSC provides urban stakeholders various values (Nasar, 2020). First of all, the value of productivity in urban operations and services will increase. Furthermore, the quality of life would get better. Finally, environmental sustainability will be better cultivated. Concerning this issue, the U4SSC ITU-T (2016) proposal has formed some KPIs for SSC. The aim is to establish standards that can be used to measure how much information and communication technologies (ICT) help to make cities more intelligent and sustainable. Additionally, the goal is to provide cities with the ability to evaluate themselves, so that they can work towards achieving sustainable development objectives (ITU-T, 2016).

The KPIs are divided into three main domains as shown in fig. 2.1. The IoT-based Waste Management System (WMS) connects and interlinks all the stakeholders such as city administration, service provider companies, truck drivers, as well as local citizens. Through advanced data-driven and data transfer technologies, cameras, sensors, actuators, and IoT controls, the current shortcoming of waste management practices can be significantly improved.

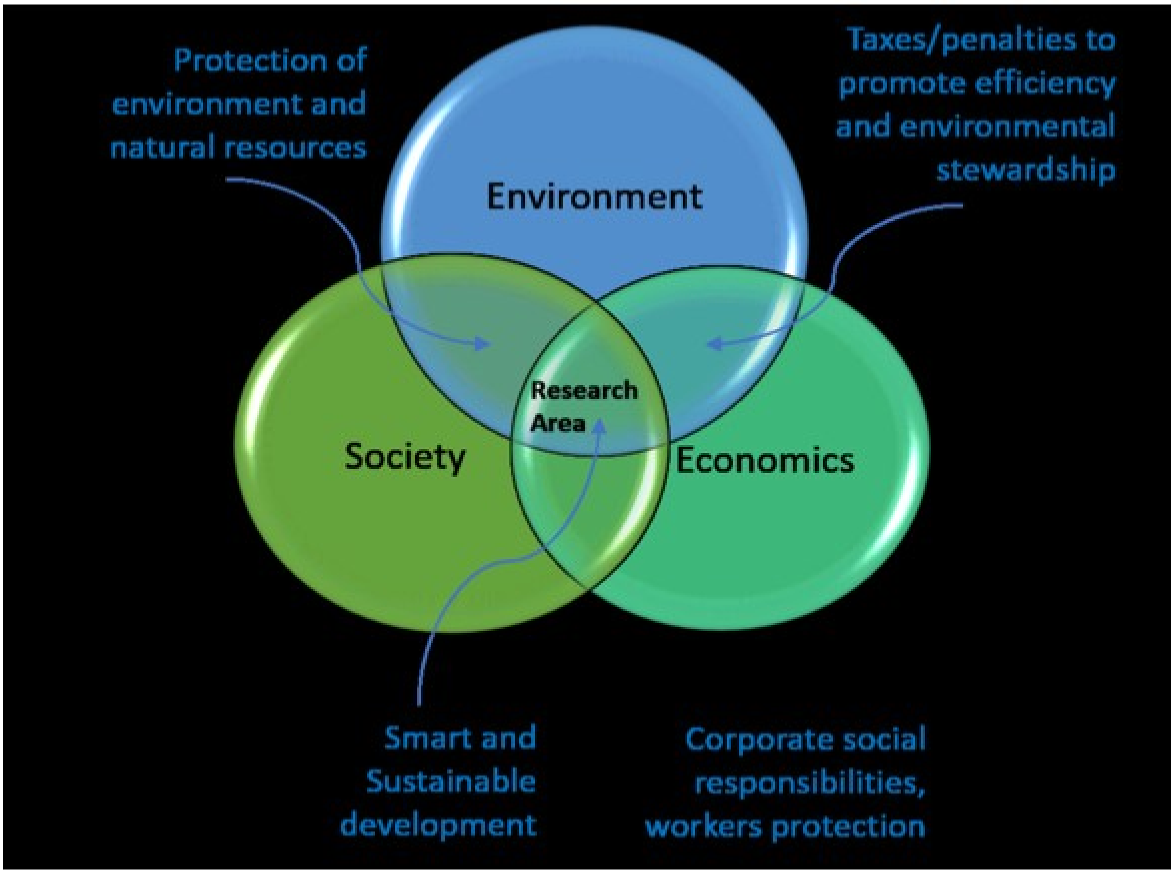


Figure 2.1: Sustainable developments domains with KPIs (ITU-T, 2016)

A conceptual model that involves a waste management system that is both smart and sustainable, as well as an optimized system for collecting and transporting the waste, has been proposed by Gutierrez et al. (2015) and Misra et al. (2018). In short, these studies examine a way to automate the waste management process by implementing IoT technologies in the process. The main goal of these studies was to reduce costs and improve efficiency in the collection process.

Gutierrez et al. (2015) suggested that an integrated design of cyber-physical systems, which incorporates various engineering disciplines and utilizes municipal wireless networks, can be an effective approach for enhancing city management in smart ways. The proposed system is built based on Geographic Information Systems (GIS), graph optimization using applied graph theory, and machine learning. The system incorporates an Internet of Things (IoT) based prototype (Smart Bin), equipped with sensors that analyze the volume of waste in trash cans or containers. The sensor data is transmitted wirelessly to the internet for analysis. This data is then used to optimize the management and strategies of waste collection logistics. The experiments compared the efficiency of two waste collection methods: the traditional sectorial (not-intelligent) approach and the dynamic on-demand based waste level status (intelligent) approach. In addition, a preliminary economic assessment was performed to determine whether the solution is financially sustainable or not. In this study performed by Gutierrez et al. (2015), 3046 trash cans were utilized and organized into 18 Collection Teams. The experimental period spanned five weeks, during which the initial week was dedicated to stabilizing the system results, while the remaining four weeks were utilized for data collection.

Zeb et al. (2019) in his study suggested an intelligent waste management system based on a smart bin which implemented an IoT sensor to control waste levels in the bin and optimize waste collection. This resulted in a significant reduction in waste collection expenses by half and increased the effectiveness of waste collection. Furthermore, Shyam et al. (2017) proposed a smart waste management system using IoT sensors to monitor waste collection and optimize garbage truck routes. That system helped to cut waste collection costs by 30% and enhance the efficiency of garbage truck routes by 25%.

Xiangru (2022) attempted to combine the emerging technology with smart bins and advanced machine learning algorithms. Xiangru (2022) claims that the applications of machine learning techniques in the field of waste management may be initiated with the deployment of smart waste bins, which are presently obtainable in the market. To monitor the waste levels throughout the city, waste management firms or municipalities employ sensors that are based on IoT technology. By utilizing the data gathered in real time from these IoT sensors, municipalities can optimize their waste collection routes, timings, and frequencies. This data-driven approach enables the estimation of likely waste bin filling rates and the identification of frequently used routes that the collecting team should follow. The article written by Xiangru (2022) presented a process for repeatedly obtaining information to enhance performance. This involves evaluating the current approach to a problem, refining it with recovered data, and then applying machine learning techniques to assess whether adding new features can improve the results. The experimental outcomes demonstrate that our proposed technique achieved superior results compared to other methods. The proposed method produced accuracy ratios of 96.1%, 92.7% cost-effectiveness, 97.1% efficiency, 89.0% tracking rate, and 91.9% and 91.6% environmental production and recycling ratios, respectively (Xiangru, 2022).

2.0.1 Discussion

The result from different studies shows that the implementation of data-driven technologies and smart bin technology in waste management practices can result in a significant reduction in costs. Also, it improves process efficiency. The implementation of smart bins with IoT sensors may provide real-time data regarding the amount of waste, whereas, ML can provide improved prediction algorithms. This would assist waste management companies in regard to optimizing their waste collection routes and manpower. Moreover, IoT sensors may automate the process of waste triage at the source by detecting it. This would certainly boost recycling consciousness and minimize the accumulation of waste in landfills.

2.0.2 Conclusion

Finally, the employment of IoT, as well as smart bin technology in waste management processes and practices within smart cities, has promising potential. This would improve the efficiency and effectiveness of waste management processes. In addition, using IoT technology would reduce the costs of garbage collection substantially. To round it off we would say more research is needed in order to exploit the potential of this technology, as well as to develop more sophisticated systems which can face the challenges of waste management in smart cities. Nevertheless, the existing studies provided a promising foundation for the development of IoT-based waste management systems in smart cities.

2.1 Theory framework/ Theory overview

In 2007, there was a significant turning point in human history when the urban population exceeded the rural population for the first time, and it is expected to climb up to 69% by 2050 (United Nations Environment Programme, 2011). This trend would present a number of opportunities such as: a higher economic growth, increase in employability, and technological advancement; however, it also has significant challenges as: the increase of produced waste per capita and pollution (Toli and Murtagh, 2020). Admitting the importance of sustainable development and a healthy environment, the UN opted for the shift towards green urbanization as a key objective (United Nations Environment Programme, 2011).

The term "Smart City" is relatively new. According to Kumar et al. (2018), a smart city refers to "A city that strives to enhance the quality of life for its residents by focusing on the environmental, economic, and social aspects of urban living. This can be done using intelligent and sustainable technologies in a competent, convenient, and innovative manner. By integrating these technologies into urban life, a smart city aims to create a better living environment for its residents." (Kumar et al., 2018). According to Lange and de Waal (2013), the phrase "smart city" primarily refers to innovations that enhance quality of living and efficiency in urban environments. Moreover, according to (Kitchin, 2013) , a smart city is primarily made up of and kept under constant observation by ubiquitous computing technology. The city's economy and governance are influenced by innovation and creativity generated by intelligent individuals. An essential component of the smart city model is the development of advanced data analytics used to comprehend, monitor, and manage the city.

The rise of the smart city concept is closely connected to cities' efforts to leverage ICT to tackle urban challenges. According to Kitchin (2013), cities that adopt ICT for purposes related to management and regulation have been identified using various labels. Many other researchers had different names for the same urban concept. Furthermore, Dutton (2019) named them wired cities, while Graham and Marvin (1999) named them: cyber cities. Ishida and Isbister (2000) on the other hand called them: digital cities, and Komninos (2002) chose the term: intelligent cities. Hollands (2008) came with the term: smart cities, and Shepard (2011) chose: sentient cities which has further been explained by Al-Kodmany (2012).

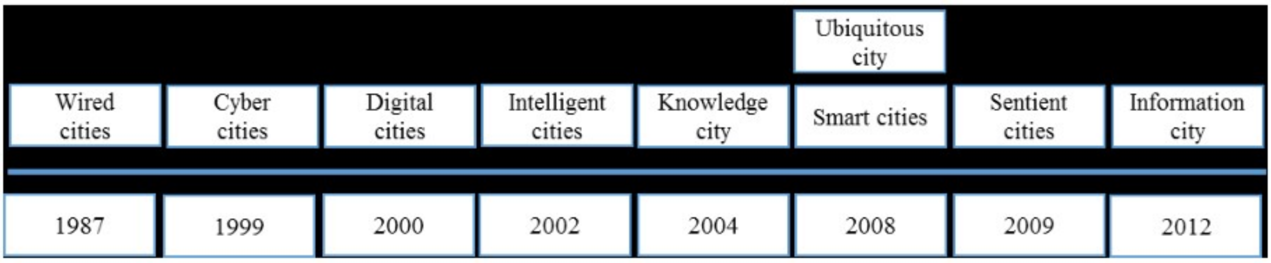


Figure 2.2: Terminologies linked with a smart city (Montes, 2020)

The history of smart cities indicates that they were created as a reaction to four key elements. First of all, the need for better tools in order to manage the rapid growth of urban areas with the continuous increase in local populations, the high demand of more efficient and effective public services, safe and sound environments, and eco-friendly cities. Secondly, the development of computing technologies and information and communication technology (ICT), initially for research and military use, then embraced by tech enthusiasts, innovative governments, and cities. Thirdly, large IT companies such as IBM, Cisco, Siemens, and General Electric recognized an untapped market and employed their technology and expertise to improve city management. Finally, citizens were interested in using digital tools and applications to enhance their cities, and with the rise of the internet, smartphones, and availability of online data, bottom-up smart city initiatives emerged (Yigitcanlar et al., 2019; Kitchin, 2013). This interest in improving cities by citizens is not new, but the emergence of digital technology facilitated their efforts.In general, the perception of a smart city is all about the extensive use of modern technology and data, in order to create an efficient, sustainable, and functional urban environment that would benefit all the citizens. Smart cities are observed to be significantly implementing (ICTs) and focusing on sustainability(Yigitcanlar et al., 2019). Smart cities typically promote sustainability in both social and environmental aspects Hollands (2008) in order to use creative and innovative approaches that leverage information and communication technologies (ICTs) to mitigate the negative consequences of human activities, such as CO2 emissions and waste (Yigitcanlar et al., 2019).

According to various studies, the global turnover of smart cities activity is projected to reach approximately 1.5 trillion dollars by 2020. This indicates a clear indication that investment and dedication to this type of urban environment will continue to expand rapidly in the years ahead (Iberdrola, 2023).

The capital spending and major investments in the technology used in smart cities has doubled since 2018. The main objective was to reduce the miscellaneous costs, improving the ecological impact, and enhancing the efficiency within urban areas. Furthermore, there is a growing demand for technology related to smart cities. The market share for this technology is predicted to grow seven times by 2030 (Iberdrola, 2023).

Other studies from the literature Vobugari et al. (2017) and Aliee et al. (2019) showed that official entities and municipalities that opted for digital transformation have not only gained knowledge and understanding for their practices and procedures, but also achieved competitive advantage over untransformed cities. Digital transformation in smart cities is made of four main components which are data, people, digital technologies, and their interrelationship as shown in Figure 2.2 (Ashwell, 2017). The volume, velocity, and access to data in smart cities referred to as Big data is increasing tremendously (Ashwell, 2017). Digital technologies and processes have made it easier for citizens and stakeholders to secure, store, discover, exploit, retrieve and share data (Bokolo, 2021).

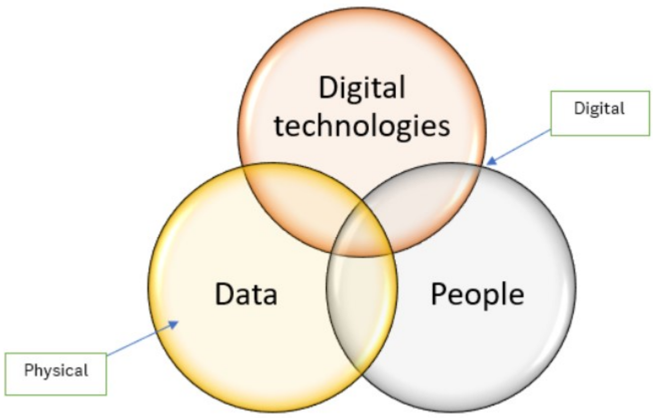


Figure 2.3: (Ashwell, 2017)

2.2 Digitization, digitalization and digital transformation

In recent years, cities worldwide have experienced a digital transformation as part of their development into smart cities. In the course KDBA140 at our institution Inland Norway University of Applied Sciences in Kongsvinger we had a guest lecturer who told us about the three different levels of ambitions regarding the digital transitions. These are the following ambition levels according to Christensen (2022), "The lowest level is digitization which is the transition from analog to digital representation. The next ambition level is high and called digitalization. This is the transition from heavy manual processes to new automated/optimized processes using digital technology. Next level of ambition is considered very high and called digital transformation. This is when digitization also entails change in the company's business model and/or radical change of the operating model using a modern and integrated application portfolio."(p. 17). In our case regarding waste management systems this will be considered as the highest level of ambition which is digital transformation for municipalities or companies. Digital transformation in smart cities has substantial implications for citizens, businesses, and local governments, and it has the potential to reform the way we live, work, and interact with our environment.

2.3 Search process for relevant literature

This part of the process includes identifying relevant literature and outlining the key points from the reviewed articles. Then creating a list of obstacles, difficulties, and concerns encountered in the process of organizational digital transformation. In the course of our research, we have conducted a thorough analysis of the literature related to our thesis topic and the importance of establishing a theoretical framework. To do this we have also used some blogs and news articles that can be relevant for our thesis with the google search engine. Further to find main theoretical resources we have looked for articles, books, magazines, videos, and other master's theses using sources such as Google Scholar, OpenAccess databases, and Oria database.

Our goal was to identify previous research in the field of waste management and smart cities, with a focus on finding academic journal articles that discuss barriers to reduce the cost of waste management. Our research topic involves the implementation of IoT devices to achieve cost savings in waste collection, and we aimed to locate the most relevant literature on the subject. Keywords are crucial in locating the most relevant literature, so we used the search term "IoT waste management system" and added subcriteria such as "smart city," "machine learning," and "digital transformation," which resulted in 224 articles. Our main focus was on high-quality articles published in academic journals between the years 2015 to 2022. We primarily used English during our search as it offers a wider range of potential matches and there is a larger pool of literature available in this language. To refine our search, we used additional keywords such as "cost efficiency," "digitalization," and "smart bin." We also searched for articles relevant to the theoretical framework of our thesis. For our citation management, we utilized Zotero, which is compatible with Oria and Google Scholar and enables us to easily import citations. In some cases where importing was not feasible, we manually added the citations.

The search engines we utilized during our study to find relevant literature were:

Google Scholar: https://scholar.google.com	https://link.springer.com/
Oria: www.inn.no/bibliotekk	https://www.researchgate.net/
Ebscohost: web-p-ebscohost-com.ezproxy.inn.no/	https://brage.inn.no/
https://www.webofknowledge.com	https://www.google.com/
https://ezproxy.inn.no/	https://www.bing.com/
https://link.springer.com/	
https://www.researchgate.net/	
https://brage.inn.no/	

Figure 2.4

3 Data-Driven Technologies

Data-driven technologies (such as IoT, ML, and algorithms) assist users in order to derive data-driven decision-making. Also, a Smart city may not be sustainable without embracing the advantages of data-driven approaches. The same thing applies to waste management in a smart city.

In general, IoT is about the ability to communicate among distributed sensors with the help of connections and integrations with the Internet. This sensor integration provides accurate information for analysis which improves the budget and efficiency. One may wonder how this technology has actually evolved over years. The first official recognition of the IoT was when Kevin Ashton introduced the term back in 1999 and is one of the founders of the Auto-ID Center in Massachusetts (Kramp et al., 2013). This is where he explained how RFID sensors could be connected to the real world through the Internet. This has subsequently led to a development of wide range of technologies. The IoT term has since evolved to be an umbrella term to have many other technologies paired with it. These technologies are continuously evolving.

According to Ahmed et al. (2018) the basic requirements for bridging and linking IoT between virtual and real world can be described as follows:
"First of all is communication. Connecting things to a network with Internet resources or between them is necessary to make use of data and services. After that comes addressing and identification where every object should be assigned a unique address and an identifier. This would make it easier to differentiate it from other objects, and enable it to be identified and located within a network. Furthermore, there is Sensing which is any kind of object that uses extended sensors in order to collect information within their environment.They record information and send data or interact directly with their environment. Moreover, there are Triggers. These are basically some Smart objects equipped with triggers that can be used to remotely control operations in the physical world. Then, there is Embedded information processing. This is basically Smart objects that are equipped with processors. They have a limited storage capacity, yet they are capable of processing the information collected by the object's sensors. Localization. This is described as being able to know

the physical position of smart objects. This is considered to be an important feature and it can be achieved using GPS. Finally, the User's Interface. This has an objective to enable users to interact with and control the object. In addition to that, it provides useful insights and live feedback on the object's status and actions." (Ahmed et al., 2018).

IoT can roughly be divided into four main components. These components can also be called layers. The first layer can be the perception layer (sensor or object) (Leverege, nd). The other layers are the connectivity layer, the data processing layer, and the interface layer (Leverege, nd). Next, we cover some major sensors used in IoT.

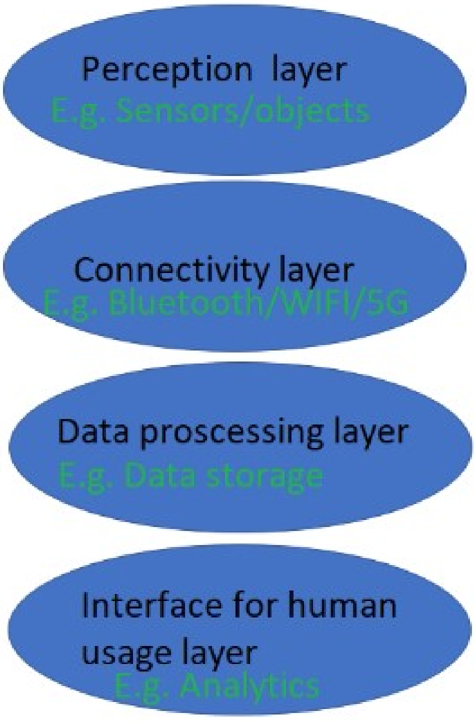


Figure 3.1: Internet of things split up in different layers simplified

3.0.1 Sensors and recording devices used in IoT

Below, we list some examples of sensors as well as devices which have been mentioned by Sehrawat and Gill (2019):"

1. Proximity Sensors: These detect the position of nearby objects without physical contact.

2. Position Sensors: These detect the presence of humans or objects in a particular

area by sensing their motion.

3. Occupancy Sensors: These detect the presence of humans or objects in a particular area.
4. Motion Sensors: These detect any physical movement in a particular environment.
5. Velocity Sensors: These calculate the changing rate in constant position measurement and position values at predefined intervals.
6. Temperature Sensors: These detect changes in heat energy and are used to measure physical changes in the body.
7. Pressure Sensors: These sense the amount of force and convert it into signals.
8. Chemical Sensors: These are analytical devices used to measure the chemical composition of the environment.
9. Humidity Sensors: These measure air temperature and moisture to provide insights about humidity in the air.
10. Water Quality Sensors: These measure ion monitoring and provide live insights about water quality.
11. Infrared Sensors: These emit or detect infrared radiations to sense some characteristics of certain objects.
12. Gyroscope Sensors: These detect tilt and angular movement in an object by measuring angular velocity.
13. Optical Sensors: These detect electromagnetic energies such as light.
14. Chemical Sensors: These provide insights by reacting to any chemical reaction, chemical substance, or a set of chemicals." (Sehrawat and Gill, 2019).

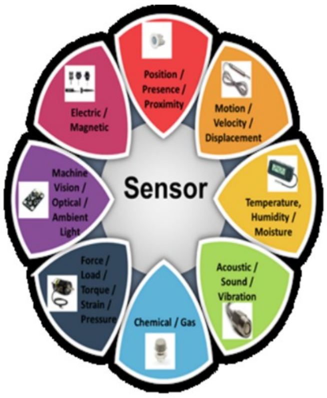


Figure 3.2: Overview of different sensors (Sehrawat and Gill, 2019)

In general, one may wonder how these sensors be helpful. Sensors can be part of every physical object for example mobile phones, traffic lights, vehicles, and in our case smart bins (Mutabazi, 2021). IoT can ease creation of a platform where all the devices can share their data to a common database and the data sent will be sent in a secure manner (Mutabazi, 2021). Further, it can be processed and then one can be able to perform data analytics on the generated data from the sensors that again can be used for data-driven decisions making (Mutabazi, 2021). Useful information, for example patterns can be extracted to improve efficiency and improve the way regarding the use of resources. With sensors placed in bins and the programming is adapted so that drivers can get useful information regarding the fill level of the bins and get optimized routes for garbage collection (Mutabazi, 2021) RFID tags can be used for labeling bins and identification, and actuators can be used for locking the lid of the smart bin when it's full (Mutabazi, 2021).

3.1 Data storage and connectivity layers in IoT

The data that is generated by IoT sensors needs to be stored somewhere. This can be stored on a local server or on a cloud computing platform service. There exist many different types of databases that can provide both reliability and scalability for handling big amounts of data. Which type of storage one ends up choosing is dependent on the application and what one wants to do with the data such as processing, speed, and analyzing features for example. Data that is generated needs to be transferred to designated storage areas. Different types of technologies are in existence today that facilitate the transfer of such data. We have different types of connectivity layers. The most common examples of connectivity in our daily lives are such protocols as Bluetooth. Bluetooth has low range and is a wireless technology with an open standard that can be used for personal area networks (Sofi, 2016). Other examples can be cellular networks, for example, 4G/5G. 5G has better capability compared to predecessors of cellular networks with better performance and efficiency which is needed in a smart city that can give better connections and experiences (Deloitte, 2022). WIFI which stands for wireless fidelity is also important to the IoT environment and has frequencies of 2.4GHz and 5 GHz, because it can carry a high amount of data, but has to compensate in terms of range (Leverege, nd).

3.2 Uses of IoT

Today many businesses are integrating different types of connectivity layers such as Bluetooth/telecom or other connections so you can for example rent an el scooter or rent a trailer by yourself without the need for an actual human being there to assist you. Everything can be done with a few clicks in an app on your phone which again can detect your location and extract other information to unlock the scooter. You can pay with your phone at a cashier with near-field communication technology (NFC) because your credit card is "virtually" loaded into your phone. NFC will in smart waste management be used for transferring data in the infrastructure (Mutabazi, 2021). If one has installed security cameras or sensors for detecting movement at home. These devices can often be linked to the internet so the security service or owner can be notified straight away on their particular device. These types of examples show how convenient IoT has become in our daily lives. In smart cities, this can be utilized for smart parking and this is where sensors allow us to know how many parking spaces that are available and how many are occupied (Sehrawat and Gill, 2019). Smart lighting is about adapting the light usage based on weather conditions or other requirements for example when movement is detected (Sehrawat and Gill, 2019).

3.3 The technology of Data Transmission

In the early development of IoT devices, the operations of battery-powered IoT devices were limited by their power supply. This constraint of battery performance is considered to be a substantial barrier to spreading the development of IoT applications (Miorandi et al., 2012). Hence, reducing the volume of energy used for data transfer and inquiry is essential (Lee and Lee, 2015; Miorandi et al., 2012) . A number of recent research projects are focused on developing passive wireless sensor networks (WSNs) and energy-harvesting alternatives to batteries. Despite the reduction in energy consumption, the need to measure and transmit data remains a critical issue (Kamm et al., 2020).

Data transfer technologies are illustrated in fig. 3.3 in terms of their range and power consumption. Each wireless network has its advantages and disadvantages. 4G and 5G telecommunications technologies are optimized for streaming a live video and substantial amounts of data, but they are energy-demanding (Cox, 2012). However, Near Field Communication (NFC) runs with passive tags and does not require a direct power supply. It instead stimulates power from the transmitted signal. Thus, it is constrained by the intensity of the magnetic field of the transmitter. The range can range from a few millimeters up to a few meters (Lee and Lee, 2015).

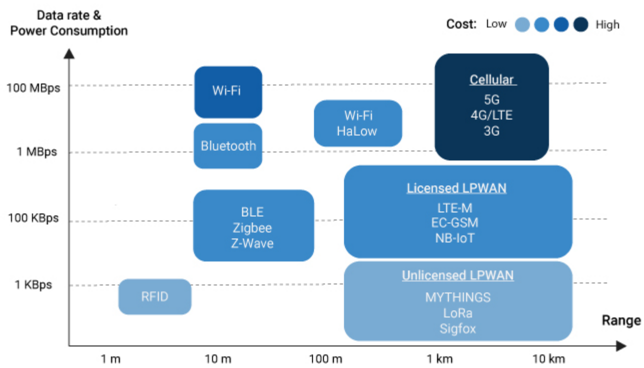


Figure 3.3: Overview of data transfer technologies(Nasar, 2020)

3.4 Machine Learning in Waste Management

The use of AI-powered tools to make data-driven decisions is getting more important than ever today. This is because of the rapid growth of the local population and the change in consumer behavior (Newton, 2022). Using ML techniques can ease the goal of managing waste properly by using several techniques and applying some models along with the help of IoT technology. One of the problems of managing the waste is improper scheduling (Khan et al., 2021). ML with the help of the IoT technology can help in finding better routes and create live schedules for waste collectors (Khan et al., 2021). Moreover, ML can be used to classify the types of waste collected with the help of Deep Learning Techniques based on Convolution Neural Networks (CNN) (Kumar et al., 2020).

In addition, some ML algorithms can help decision-makers to make data-driven decisions by providing valuable insights about the amount of waste that will be produced based on areas or population density (Nguyen et al., 2020). The ML algorithms should be combined with the use of IoT-based sensors architecture, in order to predict the amount and type of waste (Nguyen et al., 2020). Using IoT technology eased the use of different ML algorithms which would help in forecasting the amount of waste produced. One of those ML algorithms is the random forest algorithm which gave a very high accuracy in a study conducted by Uganya et al. (2022). In table 3.1, Xia et al. (2021) list an overview of several ML models used frequently in waste management.

We focused on studying the prediction capabilities of ML algorithms. In other words, we prefer to exploit the forecasting capabilities of ML in our work. In order to do it, we focus on Long Short term memory (LSTM), a Deep learning-based prediction approach. We show this approach in section 5.3. In the next section, we cover our methodology.

	ML Algorithm	Advantages	Disadvantage
Traditional ML algorithm	ANN	Good for nonlinear relationship Strong robustness and fault tolerance	Needs many parameters Lack of interpretability
	SVM/SVR	Good for tiny sample problems Avoid the local minima Low generalization error	Sensitive to missing data Sensitive to kernel selection
	DT	High interpretability High efficiency	Prone to overfitting Ignore feature correlation
	KNN	No assumption for input data Not sensitive to outliers	Need large amount of calculation Low accuracy
	ANFIS	Combine the advantages of neural network and fuzzy reasoning	Not suitable for higher dimensional features
	K-Means	Easy to implement and fast Convergence Few parameters	Easy to implement and fast Depend on the initialization of the cluster center
	RF	Reduce model variance No feature selection required	Not applicable to attribute data with different values
	GBRT/GBDT	Rank feature importance	Difficult to train in parallel
DL algorithm	CNN	Able to extract features automatically	Need parameter tuning Need a lot of sample data
	RNN/LSTM	Effective for sequence data	Need large amount of calculation height

Table 3.1: Overview of advantages and disadvantages of different ML algorithms used in waste management (Xia et al., 2021)

4 Methodology

In this section, we present a general description of our selected approaches. Recall that objective of the hypothesis relies on minimizing the incurred cost of garbage collection. Thus, we were interested to analyze how one can minimize the cost by exploiting the benefits of state-of-the-art approaches (such as IoT, Optimization, and ML). In section 4.1, we show how an IoT framework can reduce the garbage explain time - which in turn translates to minimizing the total incurred cost. In section 4.2, we explain the algorithm Travelling Salesman Problem (TSP) and how this is useful in the context of garbage collection. And, finally, in section 5.3, we show how ML can be used to improve the operational efficiency of the municipalities, where ML-assisted prediction algorithms can estimate the garbage.

4.1 IoT and cost-benefit analysis

To understand the impact of IoT, we followed the approach provided in (Misra et al., 2018). We first explain this approach. Research in (Misra et al., 2018) is an experiment on an IoT-based management system monitored by the cloud. The focus here is applying smart technology to a smart bin and using the data generated to create optimized waste management. The idea is to acquire real-time information from the garbage bins. This includes checking the filling level of the bins using sensors and providing real-time information to the municipal authorities.

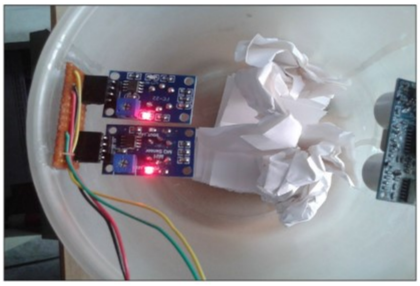


Figure 4.1: IoT sensor installed (Misra et al., 2018)

In order to understand the methodology, we briefly summarize the outcomes of (Misra et al., 2018) next. The study was conducted on nine garbage bins located at different locations in Siliguri city, India. The garbage bins are installed with IoT sensors, which provide real-time data to the municipalities. For the waste collection process, it uses an algorithm called Djisktra's algorithm which is known for the shortest path. This is being used for the shortest range between two bins for example also known as points. Also, this experiment is combined with google maps of the street city for paths. It will then be necessary to measure the distance for the shortest driving distance using the designated algorithm for being able to later compute the optimization process of the route. Given the real-time information from the IoT sensors, this approach shows that only six out of the total nine bins must be emptied and the shortest route between these bins is 13 km (D_j). The cost price per km is two dollars. The time for completing the round is 1,5 hour (t_j) and the required number of workers is two and cost two dollars for each worker per hour (E_h). Authors concluded that if there were no IoT system involved, they would have needed to empty all of the nine bins which would also increase the working time by 1.5-2 hours, and the driving route would be 20 km with a reduction in the cost of $2 \times 20 + 2 \times 2 \times 2 = 46\$$. Also, the authors concluded that 12800 $ is approximately saved per year. By implementing the Internet of Things in the bin and using the data on cloud servers for both storage and analytics the traditional methods clearly are outdated. It also shows that it has a significant battery life for the bin of a total of 186 days. With data-driven decision making the municipality in this case is able to act on the derived data. Next we present the mathematical formulation, which shows how to minimize the cost due to IoT.

4.1.1 Mathamatical Formulation

IoT sensors (Installed in waste bins) automate and improve the collection of waste management systems so that public utilities can save costs and follow operations in a sustainable way. Therefore, to address one of the research questions of the present study i.e. to conduct a cost-benefit analysis of IoT-based Waste Management solutions, we present our formulation. In this section, we will focus on investigating the changes in transportation costs, once we implement IoT-based sensors. In brief, the purpose of deploying IoT sensors is to decrease the amount of man-hour time and fuel cost. This approach eventually leads to a reduction in total incurred expenses. In addition, the implantation of IoT sensors helps in the formulation of strategies (based on available information), which reduces the need for operational staff, and results in low cost. Thus, it can be said that the cost incurred due to time can be categorized into two components, i.e. a) the travel cost and b) the labor cost. We hypothesize that a reduction in travel costs and labor costs will lead to a lowering of the total cost to public utilities. Therefore, we present the following approach motivated by (Misra et al., 2018). The total cost of the waste collection process can be defined as:

$$C = C_{\mathrm{R}} + C_{\mathrm{I}} + C_{\mathrm{F}} \tag{4.1}$$

Where: C stands for Total cost incurring in waste collection,
C_R stands for the cost incurred for covering the root to collect the garbage,
C_I stands for the cost of purchasing and implementing IoT sensors, and
C_F stands for all other fixed costs which include administrative costs, maintenance costs, internet costs, etc.

From (4.1), it can be seen that C_I and C_A are the costs that cannot be avoided. The rationale behind this is that IoT sensors are an important component and our hypothesis relies on these therefore the cost of purchasing and implementing IoT sensors (C_I) is indisputable. Administrative costs, maintenance cost, internet costs, etc. comes under the category of fixed cost (C_F), hence unavoidable and will remain fixed. However, based on the data provided by the IoT sensors, the expenditures associated with driving to various locations (C_R) to collect garbage can be reduced. Thus, our hypothesis of this section is that “Using IoT technology may reduce the value of C_R”. C_R can be further divided into two parts: a) the travel cost and b) the labor cost as shown (4.2).

$$C_{\mathrm{R}} = K_{\mathrm{D}} \cdot D_{\mathrm{r}} + nK_{\mathrm{H}} \cdot T_{\mathrm{r}} \tag{4.2}$$

Where: K_D stands for the cost per km of driving,
D_R stands for route R’s driving distance
n stands for the number of workers per garbage collection team,
K_H stands for per hour cost of labor, and
T_R stands for the time to travel route R

Although the cost distribution is shown in (4.2), it is very important to understand how long it takes to travel each route. (4.3) illustrates how TR is calculated:

$$T_{\mathrm{r}} = \left(\frac{D_{\mathrm{r}}}{a}\right) + N_{\mathrm{r}} \cdot C_{\mathrm{tc}} \tag{4.3}$$

where: a stands for the average driving speed,

N_r stands for the number of garbage bins to be collected, and

T_r stands for the time incurred in collecting one garbage bin.

From the initial analysis of the aforementioned equations (4.1) - (4.3), we observe that IoT sensors can significantly minimize the T_r. This means, the value of C_R will be reduced and in turn the overall cost C. We show the results of this approach in **??**. Once, the municipalities know how to minimize the cost due to IoT, we formulate the hypothesis on how to minimize the travel distances of the garbage collection vehicles. The traveling salesman problem, which is one of the most researched problems, is used to identify the optimal route between multiple destinations. We formulate this from the perspective of minimizing the cost of garbage collection. Next, we explain the problem of a Traveling salesman, which is widely used to optimize the travel path.

4.2 Traveling salesman problem

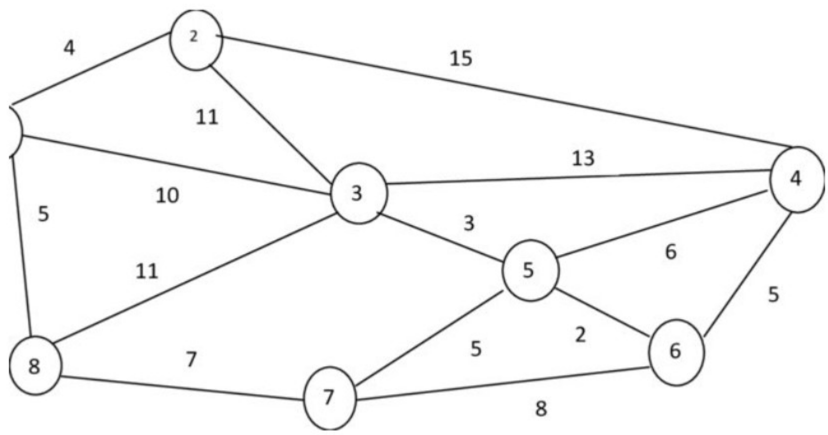


Figure 4.2: TSP graph presentation (Agbehadji, 2011)

The Traveling Salesman Problem (TSP) is a renowned optimization problem in the fields of computer science and mathematics. It requires identifying the most efficient route a salesperson can take to visit a set of cities and return to the starting point, visiting each city only once. As one of the most extensively examined combinatorial optimization problems, the TSP has numerous practical applications in transportation, logistics, and telecommunications (Jünger et al., 1994). Also, during the earlier stages of transportation research, waste truck transportation problems were often addressed using the traveling salesman problem (TSP) as it received significant attention from researchers (Fırıncı et al., 2009). Formally we explain the TSP problem next.

"Given a set of n cities and the distances d between them, the TSP seeks to find the shortest possible tour that visits each city exactly once and returns to the starting point. the objective is that this shortest path will minimize the travel cost. The graphical representation is shown in fig. 4.2".

The TSP is a well-known NP-hard problem, which means that finding the optimal solution for large instances of the problem is computationally intractable (Jünger et al., 1994). However, for small instances, solving this problem provides an optimal solution. We realized that by solving a TSP problem in the context of garbage collection, we may get a better understanding of the best route to take for waste collection based on the information received from the (nodes) smart bins.

Some approaches to solving the TSP are exact and heuristic methods. In brief, exact algorithms involve finding the optimal solution, while heuristic algorithms provide an approximate solution that is usually good enough for practical purposes (Hoffman and Padberg, 2001). Also, such approaches classify the nodes (garbage bins) via classification approach fig. 4.3.

One may minimize the travel cost of waste collection using TSP. The nearest neighbor algorithm is a popular method for solving the TSP. It works by starting at a randomly selected city and then continuing to move to the closest unvisited city until all cities have been visited. Despite being a fast and straightforward algorithm, it may not always yield the most optimal solution and can become trapped in local optima (Hoffman and Padberg, 2001). Next, we explain te basic formulation of TSP problem.

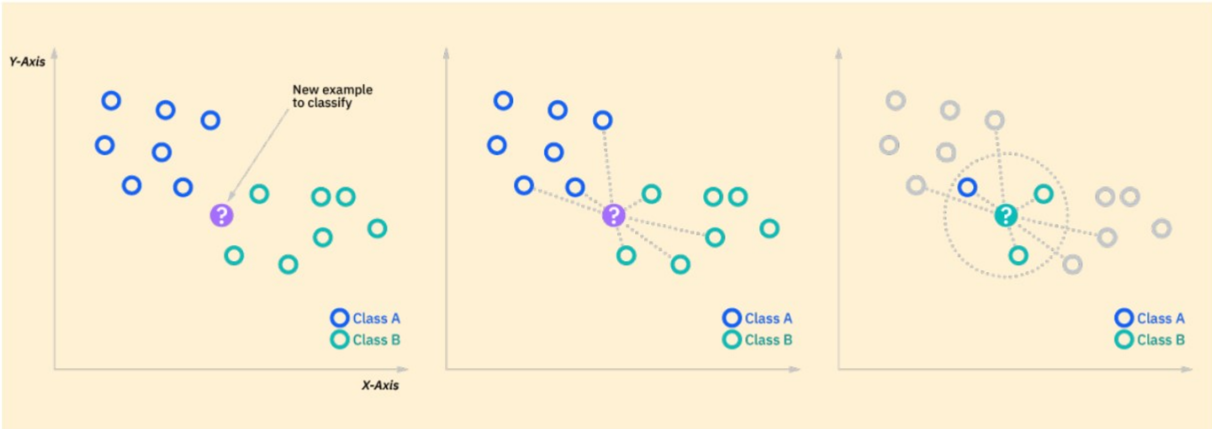


Figure 4.3: KNN to classify nodes (IBM, 2023)

4.2.1 Mathematical Formulation of TSP

The TSP can be expressed mathematically as such:

Objective function: The main objective is to decrease the total distance traveled by the salesman. This can be expressed arithmetically as:

$$\text{minimize} \sum_{i,j} d_{ij} x_{ij} \tag{4.4}$$

Where d_{ij} is the distance between city i and j, and x_{ij} is a binary variable that equals 1 if the salesman travels directly from city i to city j, and 0 otherwise.

Constraint 1: Every city has to be visited once. This can be written as:

$$\sum_{i} x_{ij} = 1 \quad \forall j \tag{4.5}$$

This constraint makes sure that each city is visited exactly once.

Constraint 2: The salesman does not have the possibility to visit a city twice. This can be expressed as:

$$\sum_{j} x_{ij} = 1 \quad \forall i \tag{4.6}$$

This constraint ensures that the salesman does not visit a city twice.

Subtour elimination constraints: These constraints are used to eliminate sub-tours, which are tours that do not include all cities. One common formulation is:

$$u_i - u_j + n * x_{ij} <= n - 1 \tag{4.7}$$

where u_i and u_j are the variables that represent the number of cities visited up to i and j respectively, and n is the total number of cities. This constraint ensures that the number of cities visited up to j is at least one more than the number of cities visited up to i if x_{ij} $= 1$. Next, we present the ML approach to estimate the future forecasting approaches of garbage.

4.3 Garbage Prediction via Machine Learning

In this section, we provide the background information of Machine Learning in the scenario of garbage collection. Various studies propose machine learning along with IoT in order to develop waste management processes. For instance, (Rahman et al., 2022) use IoT and deep learning for effective waste management. In addition, various studies propose the use of machine learning in order to predict the future increase in garbage such as (Shamin et al., 2019)-(Chen, 2022). Thus, we believe that we can also estimate the future increase in garbage in an urban environment. In order to test this approach, we acquire the publicly available dataset (over Kaggle) and tested the Deep learning model (mainly LSTM). Our hypothesis is:

"Given the time-series historical information of data, our model should be able to predict the time-ahead trajectory of the increase in the garbage. The objective is to assist public utilities in a better way so they can efficiently plan for the future scenario."

Deep Learning, a type of Machine Learning, has been significantly successful in order to develop prediction algorithms (LeCun et al., 2015). In general, Deep Learning works in the management of several applications of smart cities such as electricity grids (Fu et al., 2022), water (Wang et al., 2019), and transportation management. Also, Deep Learning is gaining significant attention in waste management (Rahman et al., 2022). Next, we explain LSTM (a deep learning approach), which can be used to forecast the increase in garbage in an urban environment.

4.3.1 Long Short Term Memory

Long Short-Term Memory (LSTM) is an effective approach of Deep Learning to predict the time series behavior of the dataset. In LSTM, the weights of the neural network rely on the adjacent cells. This means that while prediction, LSTM pays significant attention to the near-time scenario (Yu et al., 2019). An LSTM architecture can be shown in fig. 4.4.

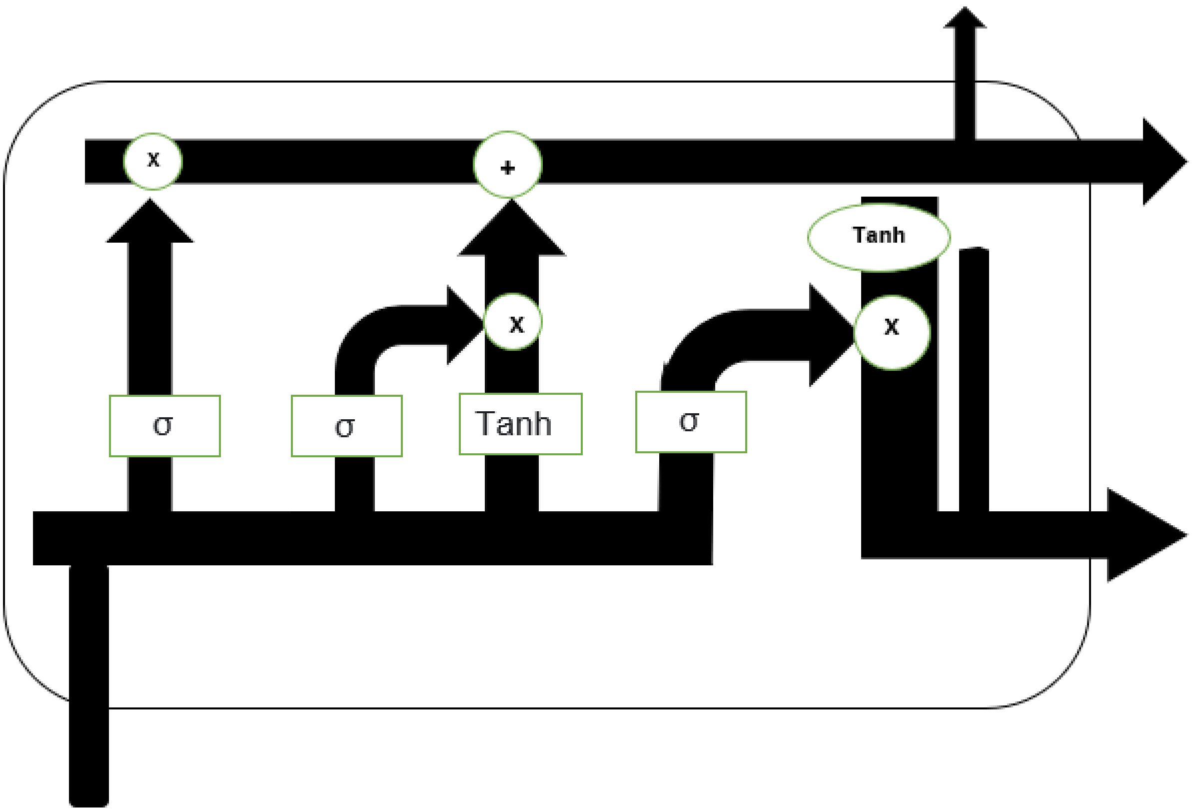


Figure 4.4: LSTM cell (Yu et al., 2019)

LSTM models preserve the dependency among the dataset. In addition, they have been successfully implemented for various machine learning applications such as energy. The LSTM uses the following equations in order to provide predictions:

$$f_t = \sigma_g(W_f x_t + U_f h_{t-1} + b_f)$$
$$i_t = \sigma_g(W_i x_t + U_i h_{t-1} + b_i)$$
$$o_t = \sigma_g(W_o x_t + U_o h_{t-1} + b_o)$$
$$\tilde{c}_t = \sigma_g(W_c x_t + U_c h_{t-1} + b_c)$$
$$c_t = f_t \odot C_{t-1} + i_t \odot \tilde{c}_t$$
$$h_t = o_t \odot \sigma_h(c_t)$$

Our objective is to use LSTM in order to predict the future increase in garbage in an urban environment. Thus, further explanation of LSTM is out of the scope of this work. Readers may refer to (Goodfellow et al., 2016) for complete details of LSTM. Next, we present our results and analysis section.

5 Analysis

In this section, we present the analysis of our approach. First, in section 5.1, we present an experiment that is derived from synthetic data motivated by a real-life scenario. In section 5.2, we show how to minimize the cost using smart algorithms such as TSP, and in section 5.3, we show how we can forecast the garbage using Machine learning.

5.1 Cost Reduction via IoT

We assume a scenario where we know the prior information about garbage bins. We collect the location of garbage bins from a real urban city infrastructure (e.g. Skedsmo). In this scenario, we already have the prior information of a) location of the garbage bins b) the distance of the garbage bins from the collection facility c) the traffic scenario, and d)the population density. It can be safely assumed that each of these garbage bins is installed with an IoT sensor, and the driver of the garbage collection truck receives this information apriori via an app. The first and foremost impact will be that this assumption greatly reduces travel distance and time. The garbage trucks at ROAF (a Norwegian garbage collection facility) use biogas as fuel. In this work, since we do not have information on the cost of biogas (generated at the Lillestrøm). Thus, we use the fuel price of 16,3 kr per liter of biogas from a gas filling station (NHO, 2022). In order to perform experiments, will use Google Maps to draw the locations of the bins and pointed out five locations (which we obtained from the Kommune resources), where each having a total amount of 10 bins. Given five locations, we have a total sum of 10 garbage collection bins.

In order to conduct the experiment we have created a map of the locations of the bins and shown in fig. 5.1. See the map, which we divided into five zones. Given the prior information, zone 4 and Zone 5 have lower population density and garbage bins are not filled, which reduces the oil and travel cost.

We identify the distances between these maps. We hypothetically assume that garbage bins are installed with IoT sensors, which are providing real-time information to the garbage collection trucks. We show the data of our computations in table 5.1. We follow the following notations in table 5.1:

Date	d KM	n	c(NOK)	$\hat{c}$	h NOK	$\hat{h}$	t	t_{iot}	$\hat{t}$	C NOK	C_{Iot}	$Saving/day()$
4/17/2023	13	30	12,78x13 = 166,14	243,42 - 166,14 = 77,28	2x200x0,2 = 80	2x200x0,6167 - 80 = 166,68	37	12	25	490.1	246.14	243.96
4/18/2023	12	20	12,78x15 = 191,70	243,42 - 191,70 = 51,72	2x200x0,35 = 140	2x200x0,6167 - 140 = 106,68	37	21	16	490.1	331.7	158.4
4/19/2023	15	20	12,78x16 = 204,48	243,42 - 204,48 = 38,94	2x200x0,4 =160	2x200x0,6167 - 160 = 86,68	37	24	13	490.1	364.48	125.62
4/20/2023	17	30	12,78x17 = 217,26	243,42 - 217,26 = 26,16	2x200x0,4833 = 96,66	2x200x0,6167 - 96,66 = 150,02	37	29	8	490.1	313.92	176.18
4/21/2023	7	20	12,78x7 = 89,46	243,42 - 89,46 = 153,96	2x200x0,2 = 80	2x200x0,6167 - 80 = 166,68	37	12	25	490.1	169.46	320.64
4/22/2023	12	30	12,78x12 = 153,36	243,42 - 153,36 = 90,06	2x200x0,3833 = 153,32	2x200x0,6167 - 153,32 = 93,36	37	23	14	490.1	306.68	183.42
4/23/2023	18	40	12,78x18 = 230,04	243,42 - 230,04 = 13,38	2x200x0,5667 = 226,68	2x200x0,6167 - 226,68 = 20	37	34	3	490.1	456.72	33.38

Table 5.1: Table shows the cost-saving scenario

- d : Total distance in KM
- n : number of bins
- c : vehicle expenses in NOK
- $\hat{c}$: reduction in vehicle expenses
- h: employee hourly expenses
- $\hat{h}$: reduction in employee expenses
- t: duration of garbage collection in minutes
- t_{iot}: reduction in time when using IOT
- C: cost of full route covering 50 bins
- C_{iot}: cost of IOT optimized routes in NOK

Figure 5.1: Bin locations from google mymaps

Thus, using (4.4), we can reduce the cost.

We plot the results of table 5.1 in order to perform the detailed analysis. From fig. 5.2, we can see that there have been significant savings in the operational cost of the vehicle. In fig. 5.3, we can see that there have been significant reductions in the cost due to reduced man-hours. Finally, fig. 5.4, we show the savings curve. Also, we show the estimated savings after employing the IoT for the hypothetical scenario. Next, we cover the travelling salesman problem.

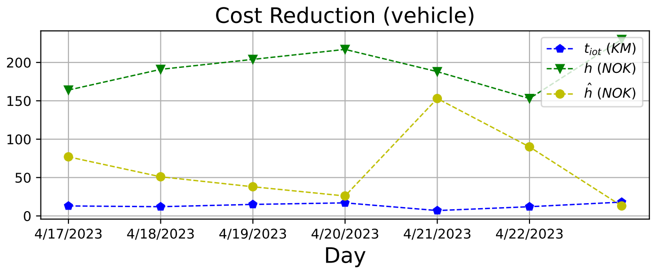


Figure 5.2: Cost reduction due to vehicles

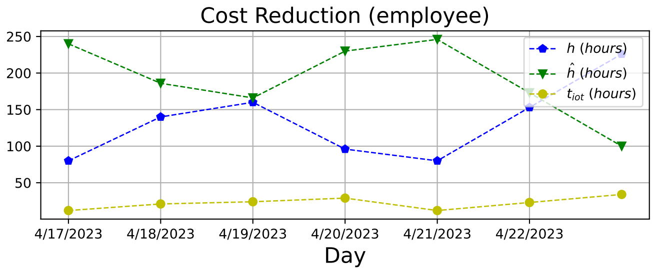


Figure 5.3: Cost Reduction due to employees

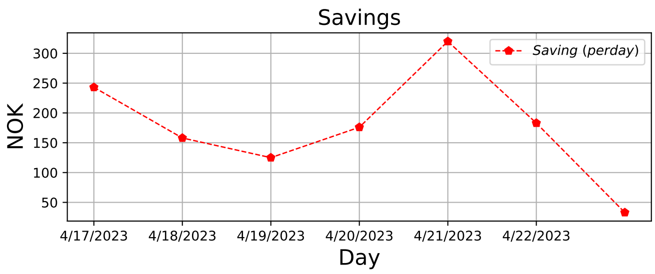


Figure 5.4: Total savings for our scenario

5.2 Travelling Salesman (Pseudocode)

The TSP problem is an NP-hard problem, which means there is no optimal solution exists for such problems. However, for small networks, where we have a limited number of nodes (garbage collection points), we can identify the best possible route to traverse the garbage collection bins. Our hypothesis is as follows:

Hypothesis: 'Given the information of the geographical location of garbage collection bins and the travel distance between, we are interested in identifying the best possible route *for garbage collection trucks which will minimize the total incurred cost of fuel. In other words, we are interested in minimizing the route traveled by the garbage collection trucks and traversing all the possible garbage bins.'*

In order to address the aforementioned hypothesis, our approach is to look at this problem from the perspective of the Travelling Salesman problem. In brief, TSP is an optimization problem, which minimizes the traveling route while traversing multiple locations. Note that, this problem is Nondeterministic polynomial (NP) hard and computationally very difficult to solve. Some of the approaches to solve the TSP problem is by using the brute force approach or nearest neighbor algorithm. In order to solve our problem at hand, we assume the location and path as shown in fig. 5.5. We formulate our problem from the perspective of TSP and refer to the location of garbage bins as nodes and the route between the garbage bins as the path. We present the below-mentioned pseudocode, which uses a greedy approach and is motivated by (Nilsson, 2003):

Pseudocode:

1. Arrange all the edges from shortest to highest.
2. Find the shortest edge and add to our tour given the aforementioned constraints (4.5)-(4.7) that it doesn't create the cyclic route.
3. Check if we cover all the edges. If the edges are not covered, repeat step 2.
4. Compute the cost function (4.4)

The aforementioned Pseudocode selects the shortest edge and adds it to the travel path.

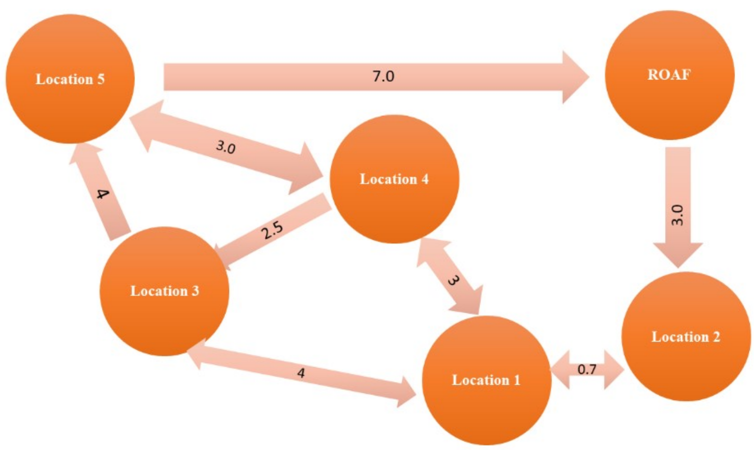


Figure 5.5: Our TSP problem

Assume that the garbage bins are located in densely populated areas. Which also have significantly high traffic on the streets. One can use the aforementioned pseudocode in order to identify the trajectory of the shortest travel path, which will eventually minimize the fuel cost. The implementation code of this approach is available open source.

5.3 Garbage Prediction via Machine Learning

In this section, we show how to use machine learning in order to predict the increase in garbage in the city environment. We collect the publicly available dataset provided by (Mudannayake et al., 2022). The dataset provides information of time-series data of garbage in tons for the city of Boralesgamuwa, Sri Lanka. The precise and accurate prediction also plays a significant role in the garbage collection utilities, therefore, we propose a Machine Learning based approach driven by Recurrent Neural networks. and explained in sec (4).

Model Information: We use the extension of the Deep learning model, mainly Recurrent neural network, in order to predict the probable increase in garbage over the years. Our model uses the tensorflow of Python in order to implement the Deep Learning model. We use the Long Short term memory (LSTM) model of Deep Learning in order to predict the rise in garbage over the years. Our model consist of following hyperparameters:

Table 5.2: Hyperparameters

Hyper Parameters	
Number of neurons in input layer	4
Number of layers	2
Number of neurons in hidden layers	4,4
Data Split (training - test)	67% - 33%
Optimizer used	ADAM
Loss	Mean Squared Error
Dropout	0.2
Scaling	MinMax
Epoch	300

The aforementioned table shows the hyperparameters of our model. We use two layers of LSTM, in order to predict the possible increase in garbage. As mentioned in machine learning literature, we split the dataset in training and test scenarios. Note that, our LSTM model is not aware of the test data, and it is merely trained over the provided

Table 5.3: Training Losses

Training Losses	
Mean Square Error (MSE)	0.0366
Mean Absolute Error (MAE)	0.0368
loss	0.0028

training dataset. Also, for improved training purposes, we use the scaling in our dataset. Scaling is the approach which potentially avoids the polarization in the data and trains the neural network weights in an optimal way. We train the model for 300 epochs and monitor the val_loss. Finally, at the end of the learning process, we restore the weights of the mode. The following figure shows the training parameters obtained from the end of epochs for our scenario:

```
Epoch 294/300
1997/1997 - 9s - loss: 0.0028 - mean_absolute_error: 0.0368 - val_loss: 0.0027 - val_mean_absolute_error: 0.0419 - 9s/epoch - 4ms/step
Epoch 295/300
1997/1997 - 10s - loss: 0.0028 - mean_absolute_error: 0.0367 - val_loss: 0.0027 - val_mean_absolute_error: 0.0416 - 10s/epoch - 5ms/step
Epoch 296/300
1997/1997 - 10s - loss: 0.0028 - mean_absolute_error: 0.0364 - val_loss: 0.0027 - val_mean_absolute_error: 0.0426 - 10s/epoch - 5ms/step
Epoch 297/300
1997/1997 - 8s - loss: 0.0028 - mean_absolute_error: 0.0364 - val_loss: 0.0029 - val_mean_absolute_error: 0.0439 - 8s/epoch - 4ms/step
Epoch 298/300
1997/1997 - 9s - loss: 0.0029 - mean_absolute_error: 0.0368 - val_loss: 0.0027 - val_mean_absolute_error: 0.0424 - 9s/epoch - 5ms/step
Epoch 299/300
1997/1997 - 9s - loss: 0.0028 - mean_absolute_error: 0.0364 - val_loss: 0.0028 - val_mean_absolute_error: 0.0429 - 9s/epoch - 4ms/step
Epoch 300/300
1997/1997 - 9s - loss: 0.0028 - mean_absolute_error: 0.0366 - val_loss: 0.0028 - val_mean_absolute_error: 0.0429 - 9s/epoch - 4ms/step
```

Figure 5.6: The training process of LSTM algorithm

Next, we show the training loss. Ideally, a machine learning algorithm should minimize the training loss. We also observe the similar phenomenon and show our training loss:

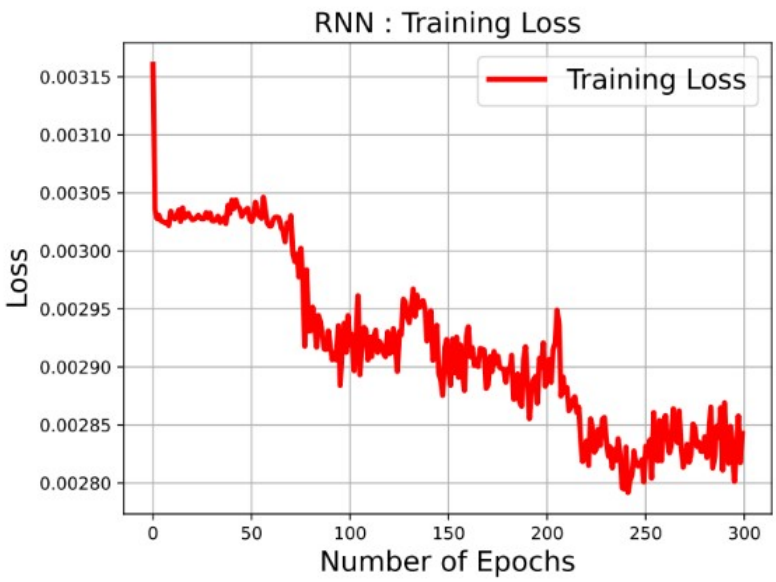


Figure 5.7: This curve shows the training loss of the proposed LSTM architecture shown in table 5.2

Next, we compare the results of the training loss and test loss. The following figure shows how the training loss of LSTM performs with the test loss.

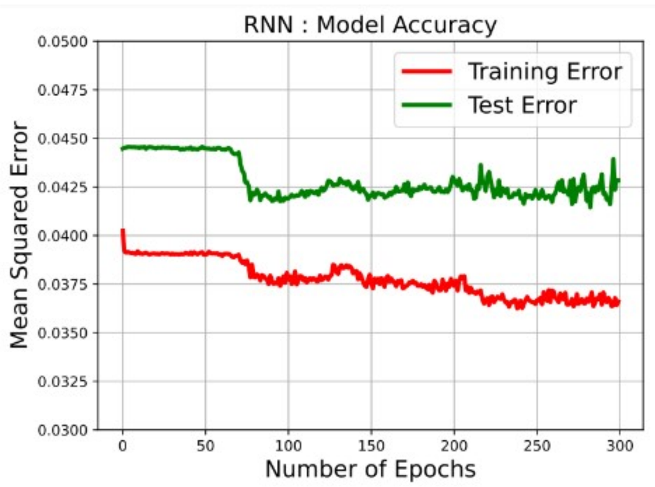


Figure 5.8: Caption

Notice that Mean Squared error of both the losses are in the range (0.075). We also compute the Mean Absolute Error between the predicted values and real values via error matrix Mean Absolute Percentage Error:

$$MAPE = \frac{\sum_{i=1}^{n} \left| \frac{y_i - \hat{y}_i}{y_i} \right|}{n} \tag{5.1}$$

where y_i is the true value of the garbage and $\hat{y}_i$ is the time-ahead predicted value. We observed an error of 0.0366 or 3% in the predicted value and true values. In the next sections, we conclude our thesis followed by discussions and results.

6 Discussion

As the world is moving towards embracing technology-driven smart solutions for smart cities, we believe that its good opportunity to investigate such developments. Thus, we focused on one of the most important challenges i.e efficient and cost-effective waste management. Furthermore, we focused on how to optimize the cost of waste collection using IoT technology and how to reap the cost-benefit of implementing such technology in urban areas. To answer these questions, we looked at different approaches based on previous research.

By implementing data-driven technologies (such as IoT and Machine learning) in Smart garbage bins with interconnected sensors, our findings show that municipalities can significantly improve the overall waste collection processes, improve efficiency, and minimize costs. This is done by optimizing routes and planning the schedules based on live data gathered from the connected smart bins. Costs related to fuel and workforce will be reduced as the energy and time consumed related to this process would be optimized. These demonstrate that by implementing IoT technology in the process of waste management, the city would be one step forward to achieving sustainability. We believe, our findings corroborate the results of Gutierrez et al. (2015). In short, Gutierrez et al. (2015) suggested that an integrated design of a data-driven approach is effective for city management in smart ways. However, this might not be beneficial in the short run. We realise that investments in the IoT space would certainly enhance the quality of life of the citizens. Moreover, embracing IoT and ML will be cost effective in the long term.

From the perspective of Norway, we observed that companies have already started to embrace data-driven approaches, however, still there is a need to acquire data in a relevant format. Thus, we focused on the approach which is motivated by real-life examples. We believe, this approach, when integrated in the realistic scenario should provide the similar results.

A significant barrier, however, faced us when we were advancing on our research. That was finding relevant data. The IoT devices and Smart Bins are not being used in Norway, and the route data was not communicated to us after approaching the local third party companies and municipalities responsible for waste collection, hence, we could not design an existent model. Therefore, we designed a model that imitated a hypothetical route using google My Maps. We opted to use the TSP approach and find out the best route to take for waste collection. We followed the pseudocode, which uses a greedy approach, and is motivated by Nilsson (2003). In order to learn more about the amount of waste to be collected in urban cities, we took an example of the city of Boralesgamuwa in Sri Lanka. We collected the publicly available dataset provided by (Mudannayake et al., 2022). The dataset provides the information of time-series data of garbage in tons in the city. This helped us to propose a Machine Learning based approach driven by Deep Learning. We used the Long Short-term memory (LSTM) model of Deep Learning in order to predict the rise in the garbage over the years. We have opted for using LSTM because it has been successfully implemented for various machine learning applications for prediction such as energy.

6.1 Future scope of the study:

Our research focused mainly on optimizing the waste collection routes in order to avoid extra use of fuel and manpower in the process. We primarily focused on identifying how to use IoT, algorithms, and ML in the efficient management of garbage collection. At the same time, we focused on minimizing the total incurred cost. We believe, from the theoretical analysis, the above-mentioned approaches can significantly minimize the cost and assist municipalities to plan in timely manner. However, during this study, we did not focus on the implication of the climate in the process and how the cold weather of Norway would affect the connectivity of the IoT devices. Furthermore, we did not research the implications of the climate of Norway on the manpower used to collect the waste. We have in addition to that assumed that the cost of implementation of IoT devices and maintaining them is minimal as the technology is advancing rapidly. This assumption is based on our reading which is related to the topic and which confirms the convenience of implementing such technology today.

7 Conclusion

In this work, we show how the municipalities (kommune) can minimize the total incurred cost of garbage collection. We formulated a hypothesis that a combination of IoT, Smart algorithms, and Machine Learning can significantly minimize the total incurred cost of garbage collection. Through, our literature study, simulated data, and numerical experiments, we observe that a) IoT can be a significant tool to minimize the cost by saving garbage collection time, b) Smart algorithms can provide efficient scheduling of the garbage collection vehicles which could optimize the traveling route, and c) ML can efficiently use to predict the future amount of garbage in the area of interest which in turn assist municipalities in better planning. Furthermore, we presented a framework of how to use the aforementioned approaches in order to minimize the total incurred cost. We concluded that the decision driven by employing the aforementioned techniques can significantly minimize the total incurred cost for municipalities. Moreover, by using IoT, smart algorithms, and ML, municipalities can significantly improve and plan the garbage collection process efficiently and effectively.

7.1 Boundaries/Limitations for the research

IoT is a wide topic and therefore we have tried to narrow it down to focus on IoT in waste management particularly. This thesis builds on previous research, which also sets the framework for our thesis. By adopting this more specific lens, our research endeavors to identify the most promising avenues for leveraging IoT technology to optimize waste management systems. The boundaries further in this thesis is that we in the beginning were trying to access data from different municipalities and third parties' stakeholders in Norway, but unfortunately it was hard to acquire data that was relevant for our thesis. Most were not able to provide data at all. And when some did have data, it was not highly relevant for our thesis, or the amount of data was not sufficient. Then because of the issue related to data we had to take another approach to the thesis.

7.2 Recommendations:

To better understand the implications of our findings, future studies could address the question of climate implication on the route optimization as well as on the IoT devices. Most of the previous research has been conducted in warmer climates, and hence it is recommended to look further into this variable.

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Appendix

```
#This script shows - how one can develop prediction models
   via Recurrent Neural Networks (RNN). This program
   predicts the garbage.

# Reference:   https://arxiv.org/pdf/1909.00590.pdf


import numpy as np                # Import Numpy for
   mathamatical computations
%matplotlib inline
import matplotlib.pyplot as plt
from pandas import read_csv  # import the data files
import math

import tensorflow as tf        # import tensorflow
from tensorflow.keras.models import Sequential
       #lib which hosts DL
from tensorflow.keras.layers import Dense

from tensorflow.keras.layers import LSTM, Dropout

from tensorflow.keras.optimizers import Adam
from tensorflow.keras.callbacks import EarlyStopping
from tensorflow.keras.callbacks import TensorBoard

from sklearn.preprocessing import MinMaxScaler
       #To normalize the data
from sklearn.metrics import mean_squared_error
#import MAPE
```

```
# convert an array of values into a dataset matrix

def create_dataset(dataset, look_back=1):

    dataX, dataY = [], []

    for i in range(len(dataset)-look_back-1):
        a = dataset[i:(i+look_back), 0]
        dataX.append(a)
        dataY.append(dataset[i + look_back, 0])
    return numpy.array(dataX), numpy.array(dataY)


/----------------------------------------------------------------------

import numpy

# fix random seed for reproducibility
numpy.random.seed(7)
# load the dataset
dataframe = read_csv('DATA.csv', usecols=[3],
   engine='python')
dataset = dataframe.values
dataset.shape

# normalize the dataset (Preprocessing)
scaler = MinMaxScaler(feature_range=(0, 1))
dataset = scaler.fit_transform(dataset)
# split into train and test sets
train_size = int(len(dataset) * 0.67)
test_size = len(dataset) - train_size
```

```
train, test = dataset[0:train_size,:],
    dataset[train_size:len(dataset),:]
# reshape into X=t and Y=t+1
look_back = 3
trainX, trainY = create_dataset(train, look_back)
testX, testY = create_dataset(test, look_back)

/----------------------------------------------------------------------

# *********This is an LSTM MODEL******************
trainX = numpy.reshape(trainX, (trainX.shape[0],
    trainX.shape[1], 1))
testX = numpy.reshape(testX, (testX.shape[0],
    testX.shape[1], 1))


# create and fit the LSTM network
batch_size = 1
model = Sequential()
model.add(LSTM(4, batch_input_shape=(batch_size, look_back,
    1), stateful=True, return_sequences=True))
model.add(LSTM(4, batch_input_shape=(batch_size, look_back,
    1), stateful=True))
model.compile(optimizer='ADAM', loss='mean_squared_error',
    metrics = ['mean_absolute_error'])
monitor = EarlyStopping(monitor='val_loss',
    min_delta=0.0001, patience=7, verbose=1, mode='auto',
    start_from_epoch= 10, restore_best_weights=True)
model_history = model.fit(trainX, trainY, epochs=300,
    validation_data = (testX, testY), callbacks=[monitor],
    batch_size=batch_size, verbose=2, shuffle=False)

```

```
%------------------------------------------------------------------------
%matplotlib inline
loss = model_history.history['loss']
epochs = range(1, len(loss)+1)

hfont = {'fontname':'Arial'}
plt.plot(loss, color='red',linewidth=3)
plt.title('RNN : Training Loss', fontsize=16, **hfont)
plt.ylabel('Loss', fontsize=16, **hfont)
plt.xlabel('Number of Epochs', fontsize=16, **hfont)
plt.legend(['Training Loss'], loc='upper right',
   prop={"size":16})

plt.grid()
plt.tight_layout()
plt.savefig('trainingLoss.pdf')

%------------------------------------------------------------------------
# make predictions
trainPredict = model.predict(trainX, batch_size=batch_size)
model.reset_states()
testPredict = model.predict(testX, batch_size=batch_size)
# calculate root mean squared error
trainScore = math.sqrt(mean_squared_error(testPredict[0],
   trainPredict[0]))
trainScore
```

Listing 1: Python script