ESCUELA INTERNACIONAL DE DOCTORADO
Programa de Doctorado en Tecnologías de la Computación e Ingeniería Ambiental

A knowledge-based framework to manage plastic waste in urban environments using multi-source data

Autor:
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AUTHORIZATION OF THE DIRECTORS OF THE THESIS FOR SUBMISSION

Prof. Dr. Andrés Muñoz Ortega and Prof. Dr. Fernando Terroso Sáenz as Directors[1] of the Doctoral Thesis "A knowledge-based framework to manage plastic waste in urban environments using multi-source data" by Navjot Sidhu in the Programa de Doctorado en Tecnologías de la Computación e Ingeniería Ambiental, **authorizes for submission** since it has the conditions necessary for his defense.

Sign to comply with the Royal Decrees 99/2011, in Murcia, December 1, 2021.

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RESUMEN

Debido al continuo aumento de la cantidad de residuos plásticos a nivel mundial, la definición de políticas eficientes de planificación urbana junto con una correcta gestión y recogida de los residuos domésticos pueden ser a menudo un reto muy exigente. Muchas ciudades y países se enfrentan a menudo con una inadecuada eliminación de los residuos plásticos, como los dos países en los que se centra esta tesis: India y Filipinas. En este sentido, India tiene políticas diferentes en función de su segmentación geográfica. Dos de los estados de dicho país que se analizan con más detalle son Punjab, donde la mayoría de las ciudades no tienen un contenedor de basura adecuado, y Gujarat, donde el uso e implantación de los contenedores municipales acaban de empezar.

Esta tesis presenta un sistema colaborativo inteligente que se centra en la monitorización de los residuos plásticos a través de un enfoque novedoso para definir políticas que ayuden en el proceso de gestión de este tipo de residuos en entornos urbanos. El sistema propuesto se compone de contenedores domésticos inteligentes equipados con balanzas de peso y una aplicación inteligente para recoger y anticipar los residuos plásticos que se almacenarán en el contenedor en diferentes horizontes temporales. Por otro lado, el sistema es también capaz de genera rutas mediante un mecanismo de planificación que facilita a los recicladores la recogida proactiva de residuos en los hogares con diferentes medios de transporte. Los recicladores pueden utilizar las diferentes ubicaciones de los contenedores municipales de residuos plásticos que han sido previamente inferidas por nuestro sistema a través del análisis de datos abiertos socioeconómicos y demográficos. Este sistema inteligente ha sido evaluado en dos zonas urbanas de la India y Filipinas mostrando resultados convincentes.

Gracias a la continua promoción mundial de los datos abiertos como método para acceder a datos transparentes, este estudio también ha utilizado datos abiertos para recuperar la demografía, el número de locales dentro de diferentes categorías, el número de segmentos de calles y la ubicación de los contenedores de cuatro ciudades occidentales de referencia: Nueva York, Málaga, Madrid y Stavanger. El objetivo principal de extraer los datos abiertos de estas cuatro ciudades es determinar la distribución de las papeleras en función de las variables mencionadas. Como prueba de concepto, hemos empleado estos datos para planificar un escenario de gestión de residuos urbanos en las ciudades objetivo de Filipinas e India. La comparación de las ciudades de referencia y las ciudades objetivo también nos permite ver que las zonas de la India parecen ser más familiares, como Stavanger, debido a la distribución de los locales, y que Quezon City tiene una actividad ciudadana similar a la de Nueva York, Madrid y Málaga.

En concreto, se realizó un análisis de regresión lineal sobre los datos de las ciudades de referencia para determinar las variables relevantes y el coeficiente de determinación que mide la confianza en los modelos. También se aplicó el análisis de mínimos cuadrados ponderados a las diferentes variables obtenidas en los pasos anteriores, como la densidad de población, el número de segmentos de calles y los cuatro usos del suelo predominantes obtenidos mediante la aplicación del algoritmo de análisis de componentes principales. Con ello, se identificó el número de contenedores necesarios y propuestos en cada una de las ciudades objetivo.

Por otro lado, la recogida de residuos en la mayoría de los países sigue basándose en métodos tradicionales con horarios fijos. Esto representa un problema, ya que una recogida de residuos inadecuada e ineficaz puede provocar contaminación y polución. También pueden surgir grandes preocupaciones entre la población cuando hay un tratamiento inadecuado de los residuos plásticos debido a problemas de recogida como, por ejemplo, la irregularidad de la misma. Como alternativa, se utiliza un contenedor inteligente con una báscula de alta resolución para controlar los residuos plásticos domésticos. También se diseñó una aplicación colaborativa para gestionar la recogida de residuos domésticos en las comunidades con necesidades especiales, como residentes afectados por Covid-19, personas mayores o con discapacidad. Este desarrollo incluyó además un algoritmo para prever la generación de residuos de plástico con el fin de disponer de una ruta de recogida optimizada para los recolectores de basura doméstica. A modo general, el sistema recoge el peso de los contenedores de las casas a través del sensor de peso. Estos datos se envían a un servidor backend que incluye un panel de control para visualizar los datos recogidos por el sensor, así como un algoritmo de planificación capaz de personalizar las rutas de los recicladores registrados en el sistema para que la recogida de residuos sea proactiva y no tradicional.

Los datos utilizados para realizar las simulaciones se basaron en experimentos realizados a través de diferentes características demográficas como tipos de hogar y grupos de edad. La predicción del peso se introduce en el módulo que se utiliza para crear rutas para los recicladores. También se obtuvieron tres clústers basados en dichas características, cada uno representando un perfil particular de generación de residuos plásticos. La evaluación de la simulación se llevó a cabo en la ciudad de Quezon, Filipinas, donde se definieron ocho contenedores inteligentes domésticos y dos ubicaciones de recicladores, y cada contenedor se vinculó a un clúster particular. Se simuló un enfoque iterativo en el que se extrajo un experimento particular y se generó un número específico de subexperimentos. Los puntos de recogida junto con el registro de tiempo u horas de los recicladores se introdujeron en un algoritmo para la optimización de las rutas de recogida necesarias para los recicladores. Posteriormente, se calcula la tasa

de recogida que indica el porcentaje de contenedores incluidos en la ruta que son recogidos por los recicladores antes de que se llenen. Los cálculos de cada ruta incluyen la hora de recolección y la hora de llenado real de cada contenedor. Tres medios de transporte diferentes, coche, bicicleta y a pie, fueron estudiados para estudiar dicha tasa de recogida. Los resultados muestran que la solución alcanzó una tasa de recogida media del 80%. Además, cuando se utilizan bicicletas y coches, las tasas de recogida aumentan con el mayor número de predicciones de contenedores.

Con la integración del módulo de planificación urbana y el módulo de composición de rutas y contenedores inteligentes, los resultados muestran una tasa de recogida media superior al 80% para bicicletas, coches y a pie como medio de transporte. También se puede observar que el uso de los recicladores y los contenedores de residuos municipales en la misma zona, facilitaría un sistema sostenible que permite el uso de bicicletas y el desplazamiento a pie a las casas y los contenedores en lugar de en coche.

En definitiva, se ha conseguido una solución colaborativa que ayuda a distintos colectivos en la recogida de los residuos plásticos domésticos. Así, se propone un contenedor inteligente ligero de alta resolución para captar y pronosticar la cantidad de residuos plásticos en los contenedores de cada hogar. Además, se definen diferentes técnicas inteligentes para generar rutas optimizadas para los recolectores de residuos domésticos y los recicladores registrados. Esto les permitirá llevar a cabo una recogida de residuos eficiente. También se determina el número de contenedores de plástico necesarios en una zona específica a través de datos abiertos y diferentes variables relacionadas con la planificación urbana y la gestión de los plásticos extraídos de ciudades referentes en la gestión de residuos urbanos.

KEYWORDS: Urbanismo, Computación de Estadística, Materiales plásticos, Diseño de Sistemas Sensores

ABSTRACT

With the continuous increase of the amount of plastic waste, efficient urban planning policies together with the proper management and collection of household waste can often be a demanding task. Many cities and countries are often faced with the inadequacy of plastic waste disposal such as the two countries which are focused on in this thesis: India and the Philippines. India has a lot of different policies based on its geographical segmentation. Two of the states which are further discussed are Punjab and Gujarat. Punjab wherein most cities do not have a proper disposal bin and in Gujarat where the use and implementation of municipal bins have just started.

This thesis presents an intelligent collaborative system that focuses on monitoring plastic waste through a novel approach to define policies to help in the process of management of this type of waste in urban settings. The proposed system is composed of simple smart bins equipped with weight scales and a smart application to collect and forecast plastic waste generated at different time horizons. The application also generates routes based on a route-planning mechanism that makes is easier for waste pickers to collect waste from the households with different means of transport. The waste pickers can use the different municipal plastic waste bin locations that have bee previously inferred by our system through the analysis of socio-economic and demographic open data. This intelligent system for plastic waste management has been evaluated on two urban areas of India and the Philippines showing compelling results.

Thanks to the continuous global promotion of open data as a method of gaining access to transparent data, this study has also used open data to retrieve the demographics, number of venues within different categories, number of street segments, and the location of bins of four western cities, namely New York City, Malaga, Madrid, and Stavanger. The main aim of retrieving these four cities' open data is to determine the distribution of bins according to the abovementioned variables. As a proof of concept, we have employed these data to plan an urban waste management setting in the target cities in the Philippines and India. The comparison of the reference and target cities also allows us to see that the Indian areas appear to be more family-friendly like Stavanger due to the venue distributions, and Quezon City has similar number of human activities in New York, Madrid, and Malaga. A linear regression analysis was performed on reference city data to determine relevant variables and the coefficient of determination which measures the confidence in the models. Weighted Least Square analysis was also applied to the different variables obtained in the previous steps such as population density, number of street segments, and the four

predominant land use obtained through the principal component analysis algorithm application. With this, the number of bins needed and proposed for the target cities were identified.

On the other hand, waste collection in most countries is still based on traditional methods with fixed schedules. It represents a problem as improper and inefficient waste collection can result to pollution and contamination. Major concerns can also be raised when there is improper treatment of plastic waste due to collection issues such as irregularity of collection, for example. As an alternative, a simple smart bin using a high-resolution weight scale is used to monitor household plastic waste. A collaborative application was also designed to manage the collection of household waste in the communities with special needs, such as Covid-19 affected residents, elderly people, and people with disabilities. Additionally, an algorithm that can be used to forecast the generation of plastic waste in order to have a collection route that is optimized for residential garbage collectors. The overview of the system includes the system capturing the weight of the bins from houses through the weight sensor. These data are forwarded to a backend server that comprised of dashboard to visualize collected sensor data. A predictor that customizes routes for registered waste pickers is also used for the collection to be proactive and not traditional.

Data used to perform the simulations were based on experiments made through different demographic characteristics such as types of household and age groups. The weight prediction is then fed to the module which is used to create routes for waste pickers. Three clusters were also obtained based on the features, and they represent a particular user profile in terms of plastic waste. The evaluation of the simulation was performed on Quezon City, Philippines, where eight household smart bins and two waste picker locations were defined, and each bin were linked to a particular cluster. An iterative approach was simulated where a particular experiment was extracted, and specific number of sub-experiments was generated. Pickup points along with waste pickers time or hours log were fed to an algorithm for optimization of route planning to compose collection routes necessary for the waste pickers. Collection rate which indicated the percentage of bins included in the route that is collected by the waste pickers is calculated. The calculations of each routes include the collection hour and actual filling hour of each bin. Three different means of transport such as by car, by bike, and on foot were primary means of transport based on the collection rate. The results show that the solution achieved an average collection rate of 0.8. Additionally, when using bikes and cars, the collection rates increase with the larger number of bins predictions.

With the integration of the urban planning module and the smart bin and route composition module, the results show an average collection rate of over 80%

for bikes, cars, and on foot as a means of transport. It can also be noted that with the use of waste pickers and municipal waste bins in the same area, it will be a sustainable system which supports the use of bicycles and travelling from houses and bins on foot instead of by car.

All in all, a collaborative solution that assists different groups with their household plastic waste collection was attained. A lightweight high-resolution smart bin to collect and forecast the amount and generation of plastic waste in each household bins is proposed. Different intelligent techniques were defined in order to generate optimized routes for residential waste collectors and registered waste pickers. This will allow them to pursue efficient waste collection. In addition to that, the number of plastic bins needed in a specific area was determined through open data and different variables related to urban planning and management of plastic in the countries with existing placement of municipal plastic waste bins and through statistical analysis.

KEYWORDS: Urban Planning, Statistical Computing, Sensor System, Artificial Intelligence, Human Ecology

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1.1. MOTIVATION OF THE STUDY

Plastics are now covering most of our urban and natural ecosystems. As stated by Kenyon and Kridler (1969), the first evidence of plastic accumulation was found through the examination of the gut content of seabirds in the 1960s. Up until today, little progress has been made in reducing plastics but large progress in knowing the effects they have on the environment (Barnes et al., 2009).

According to Reddy and Sasikala (2012), the continuous increase of plastic waste in our cities can be harmful not only physically but also mentally, for example with cases related to depression, anorexia, and restlessness, among others. In India, 90 percent of solid waste including plastics is usually dumped in the open but reusing plastics has been known as a positive reinforcement in order to lessen plastic waste in a community (Banerjee, Srivastava, & Hung, 2014). According to the previously mentioned authors, recycling plastics through melting them and making a reusable product or using it for roads or as fuel is also a big help. However, it can lead to complications because of the incompatibility of the plastic polymers and their different melting points. There are solutions made available to help fix the problem of the accumulation of plastics. For example, as stated by Hopewell, Dvorak, and Kosior (2009), it is better if we throw our plastics in a landfill. On the contrary, Jindal (2019) stated that landfill is the least favoured option for a public or private initiative. This author also stated that there are many other ways to reuse plastics, such as using plastics for road constructions, mixed with cement, or turning plastic into fuel.

Recently, due to the COVID-19 pandemic, the production and distribution of plastics have increased significantly. During this time, every individual needs face masks, face shields, or personal protective equipment to protect against the transmission of the disease (Sunjaya & Jenkins, 2020). Therefore, with the growth of plastics as seen in today’s time, efficient plastic waste management is necessary. However, because incineration or landfills is the most common way of eliminating plastic waste, finding an efficient way to manage plastic waste, without mistreating the environment additionally is indispensable (Singh & Sharma, 2016). In this context, this thesis aims to provide a knowledge-based framework to improve the management of plastics both in cities and in households.

1.2. INFORMATION TECHNOLOGY COMPONENTS FOR PLASTIC MANAGEMENT

In this section, sensors, open data, and machine learning are defined and explained through related studies that have used these technologies for plastic waste management. The combination of these Information Technologies (ITs) will be used in this thesis for the development of a knowledge-based framework to manage plastic waste in urban environments.

1.2.1. Sensors

Sensor technologies and systems are normally used in medical applications, environmental systems, traffic and parking monitoring, agriculture, and many more to detect different types of characteristics such as temperature, motion, location, etc., and convert them into readable outputs (Dener & Bostancıoğlu, 2015). An example of the use of sensors in waste management is in segregating waste. In a study by Elhassan, Ahmed, & AbdAlhalem (2019), a sensor system was used to separate waste into five different types-paper, plastics, metal, glass, and the rest. Two capacitive sensors were utilized to separate paper from plastic, and metal sensors were also used. Glass waste was separated through an infrared sensor, and the remaining waste, which is organic waste, was what was left in the containers.

The efficacy of these sensors has been proven yet communities are hesitant to put this proposal into action as the number of sensors and other hardware components being used in this process is not cost-efficient. These devices are also significantly efficient and effective, especially through the integration of information and communications technology and the Internet of Things (IoT). In a study by Atzori, Iera, & Morabito (2010) and Harbers et al. (2018), the IoT approach is difficult to understand even for researchers working in a specific field. It also affects or threatens the security and privacy of data. Thus, they have created a Venn diagram to better explain certain aspects and examples of the IoT paradigm.

An example of the use of sensors together with IoT is the collection of data through sensors on roads, in rivers, railways, and other media infrastructure for Smart Earth technologies which are environmental applications under IoT (Ganchev, Ji, & O'Droma, 2014).

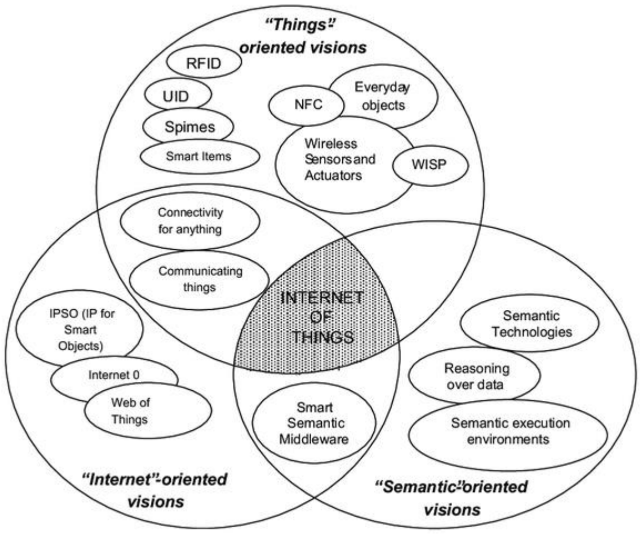

Figure 1: The IoT paradigm based on *The internet of things: a survey*

1.2.2. Open Data

Open Data is the paradigm of how data, within different contexts and domains such as scientific, administrative, demographics, among others, can be published and re-used without permission barriers. This important concept of re-use without permission is essential for further studies. In scientific research, the rate of discovery can be accelerated by better access to data (Murray-Rust, 2008). Open data in smart cities means not only the global data collected and made accessible by the government, but also it should include the sharing of data among individuals and industries (Ahlgren, Hidell, & Ngai, 2016). Furthermore, as stated by Murray-Rust (2008), open knowledge amounts to data for everyone that is free to use, re-use, and redistribute without legal, social, or technological restrictions. As a result, public data in smart cities can be used as comprehensive datasets that are integrated into technological processes related to waste management. An example of this is the use of country-level municipal waste data, population, and gross domestic product to predict future municipal waste generation in a country (Lebreton & Andrady, 2019).

1.2.3. Machine Learning

Machine Learning (ML) is a foremost branch within the Artificial Intelligence discipline. The key goal of ML is the use and development of data mining techniques and algorithms able to learn a particular task in a gradual manner as humans do. It helps improve decision-making systems based on pre-defined and static rules into more dynamic and statistically oriented, settled systems that can adapt to new data (Amershi et al., 2019). Machine Learning can be classified into three approaches: supervised learning, the most widely used type that uses training data with labels to be able to predict future outputs; unsupervised learning, which uses training data without labels to be able to recognize, group, or cluster similar data; and reinforcement learning, that uses sequences and observational data to interact for further augmentation (Jordan & Mitchell, 2015). As an example of the application of ML in waste management, in a study by Dubey et al. (2020), Machine Learning techniques were used to forecast the fill level of the bins and to cluster data to differentiate between biodegradable and non-biodegradable waste.

1.3. TOWARDS THE DESIGN OF AN INTELLIGENT FRAMEWORK FOR PLASTIC WASTE MANAGEMENT

Due to plastic waste increasing day by day, the use of IT elements as an alternative to manage the amount of plastic generated in the context of smart cities will be an essential solution. Thus, the design of an intelligent framework based on the IT components may represent a compelling solution for this task. For instance, developing a smart bin with low-cost sensors for households would be an important tool to accurately check and analyze plastic generation and management in urban areas. Likewise, open data such as the population, number of bins, their distribution in the streets, etc. of cities such as New York or Madrid can be re-used to design new urban plans for other developing cities lacking waste management infrastructures, for example, to distribute an optimal number of plastic waste containers in the streets. The starting point of this process would be urban planning for municipal waste bins in developing countries or countries with no waste containers in the streets. The designated number of bins would be generated by applying different techniques coming from the fields of statistical analysis and machine learning on open data collected in several Western cities with previous successful experience in waste management. Finally, services such as the generation of collection routes for waste pickers and volunteers for household waste and for stakeholders to collect municipal waste would be offered to provide these actors with optimal directions.

All in all, all these services can be integrated into a general framework offered to help the community, especially in Asia where the waste management policies and technologies have not been updated while solid and plastic waste production has increased (MacRae, 2012; Marks, 2019).

Figure 2 shows a general overview of the proposed intelligent framework for managing plastic waste in smart cities. The overview focuses on actors such as the households, local authorities, and the waste pickers interacting with the system in order to give or receive outputs for their own purpose such as collecting, disposing, and planning. The system consists of different processes such as intelligent modules, open data connectors, dashboards, and data storage that all revolve around smart bins which are responsible for the input and output of data. The low-cost household bins equipped with sensors monitor plastic waste, while a designed application will be used to manage the collection of household plastic waste within the communities with the help of volunteers or waste-pickers. With this data, an algorithm is applied to forecast the generation of household plastic waste. It is also to optimize routes for residential garbage collectors and waste-pickers. The municipal plastic bin distribution and placements in communities is also another process wherein local authorities retrieve data through open data in order to analyse data statistically to determine the total number of bins needed in a city.

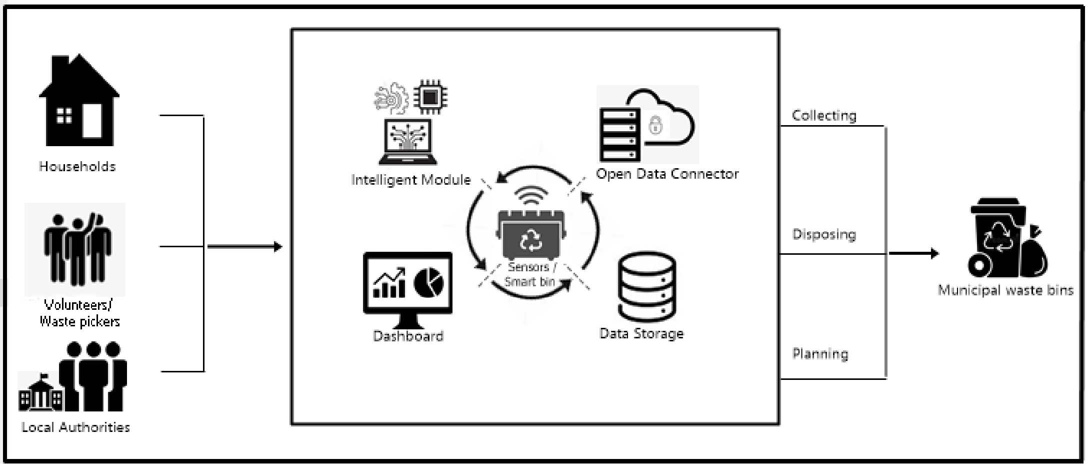

Figure 2: General overview of the proposal of an intelligent framework for managing plastic waste in smart cities.

1.4. BACKGROUND OF THE STUDY

In this section, we analyse the context in which the project developed in this thesis takes place. Recently, the control and management of plastic waste in cities have become an issue of concern to society. New urban planning and services become a necessity in order to efficiently manage waste and this process can be fostered using different IT elements and the data gathered from them. An example is the use of cellular data in order to capture city dynamics in Morristown, New Jersey. Call detail records and cellular traffic was noted for 2 months with the purpose of plotting and visualizing the activity of residents during the day and late at night. This type of collected data and visualization can be used to provide services such as optimization of waste collecting routes in the city according to this activity (Becker et al., 2011). In another example, data collected from different private and public organizations in the city was used to identify target points in a city such as physical, socio-economical, and political-institutional, in a way to plan an active and holistic plastic waste management in coastal areas (Moura et al., 2020)

In a study by Thota et al. (2018), the use of incentives is discussed for people who live in a community when they dispose of plastic waste to raise awareness about plastic waste management. Thus, a reverse vending machine called ReVa is proposed to increase recycling of plastics. This machine, when given a Polyethylene material, rewards the users with air miles. Additionally, a recycling bin that produces a positive sound and emoticon has also been developed to give a reason for citizens to recycle and be aware of plastic pollution. The bin has a proximity sensor attached inside the bin, while an LCD monitor and speakers are attached outside the bin. When the sensor detects a plastic waste is being thrown inside the bin, the LCD displays a positive emoticon (Berengueres et al., 2013). In this line, mobile applications with QR code scanners have also been proposed to determine how much a person has recycled in specific plastic waste containers (Briones et al., 2018).

Another line of work in this area is the location of plastic bins. Hence, there are mobile applications that can tell the users if the bin is empty or full through GPS and ultrasonic sensors, so the users can know the easiest way or closest bins possible. Likewise, there is an interest in finding optimal paths for stakeholders as well. In Cartagena (Spain), sensors were used to define different bin levels in order to determine when to collect the bin. An open-source platform was also used to display waste bin maps and the optimal route was calculated based on the costs of fuel consumption and the weight of the collected waste (Bueno-Delgado, Romero-Gázquez, Jiménez, & Pavón-Mariño, 2019).

In order to plan for waste management in smart cities, a bin with proximity and weight sensors can be used, as in Catania & Ventura (2014). It was determined that proximity sensors can help detect placement locations, and weight sensors to recognize the weight of the bins. This system was planned to make the collection time efficient. Data gathered from the sensors are also stored and used in a database to analyze the amount of plastic waste in a city. Another study (Vijay et al., 2008.) focuses on the location of waste bins by digitizing maps and building a road network by connecting points where bins are currently located. Additionally, to analyze if the location of the bins is precise or needed in the area, the p-median model was used. Household locations and demand for bins were also utilized in the equation. In India, due to the lack of solid waste collection bins, mathematical modelling and geographical analysis were used in order to determine the number of bins and the location of these bins (Rathore, Sarmah & Singh, 2020).

1.5. OBJECTIVES OF THE THESIS

This thesis aims to develop a framework for the holistic and intelligent management of plastic waste in urban areas of developing countries by using heterogeneous and open data sources. The specific objectives of this thesis are:

1. Planning locations of municipal plastic waste containers through open data and statistical analysis for developing cities with zero to a limited number of plastic bins.

2. Developing a smart bin based on a low-cost sensor set to monitor the fill level of the bin in household environments.

3. Predicting the weight of plastic bins and number of plastic items in the smart bin through statistical analysis.

4. Developing a framework that will store, analyze and display data acquired from the smart bin sensors for the following purposes:

    a. For the municipal authorities to analyze plastic waste trends in the region.

b. For people with disabilities, senior citizens, and Covid-19 affected residents to be able to automatically call or request for waste-picker volunteers.

c. For waste collection services and waste pickers to be able to know the location of the house where plastic waste needs to be collected and the location of the municipal bins where the plastic waste can be disposed of properly through optimal collection routes.

1.6. PUBLICATIONS

1.6.1. Main publication related to this thesis

Journal details *Sensors*
Guest Senior Editor: Dr. Raffaele Bruno ISSN: 1424-8220 Editor: Multidisciplinary Digital Publishing Institute (MDPI) Impact Factor (2021): 3.576 Category: Internet of Things Ranking: Q2 Website: https://www.mdpi.com/journal/sensors

Publication	
Title	*A Collaborative Application for Assisting the Management of Household Plastic Waste through Smart Bins: A Case of Study in the Philippines*
Issue	Sensors and Assistive Technologies for Smart Life
Year	2021
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State	Published

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1.6.2. Other publications in the PhD period

Book Series *Smart Objects and Technologies for Social Good*
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II - STATE OF THE ART

II – STATE OF THE ART

This chapter includes a discussion on the technologies that compose the proposed intelligent framework for plastic waste management. It also includes the most relevant literature reviews relating to sensors, open data, and Machine Learning.

2.1. SENSORS

2.1.1. Smart Bins

There have been multiple studies relating to the use of sensors as a way to manage plastics. According to Angin et al. (2018), using a sensor to separate trash by type is one of the best ways to segregate waste. The sensors used in the study were infrared, metal, and light, for organic, metal, or paper trash, respectively. Infrared sensors are also found helpful by other lines of research to detect if a bin is full or not for proper waste disposal. The use of different kinds of sensors with compatibility with each other has proved to be highly effective. According to Al Mamun, Hannan, and Hussain (2014), with the use of accelerometer, ultrasound, temperature, and humidity sensors, it is easy to monitor a bin in real-time. These are all in one group named Smart bin. The second group consists of the load cell that sends data from the bins through the gateway to process the data and save it in the database.

Smart bins are a combination of software and hardware components in order to manage waste through technology. Systems integrated with smart bins are normally designed with tier architecture that defines each level by its characteristics and needs. An example of this system is a three-tier architecture (See Fig. 3) in a paper by Folianto, Yeow, & Low (2015) which included sensors and gateway nodes in the first level that receive and transmit data to the second level. The backend server under the next level combines and processes data and readings. This information is then visualized and displayed in the third level to user applications.

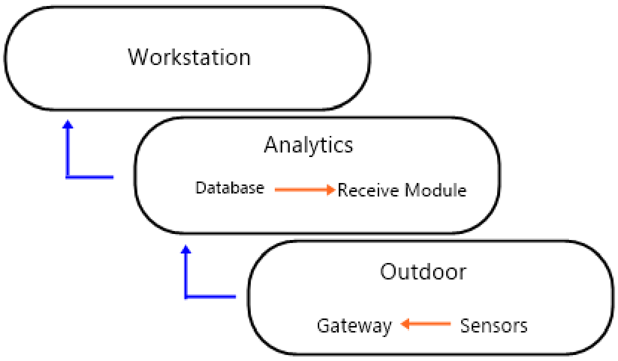


Figure 3. Smart bin architecture based on Folianto, Yeow, & Low (2015).

Additionally, some smart bins are not defined by their levels of architecture, but by the number of sensors combined and used in the bin. Smart bins are usually developed for multiple purposes such as checking the bin level if it is full or not, checking if the lid of the bin is closed or not, and many more. However, the purposes are established by the type of sensor and what it is used to detect. In a study by Al Mamun, Hannan & Hussain (2014), sensors were distributed in two groups to accurately explain and justify the results obtained. The first group consisted of an accelerometer that keeps track of the cover of the bin, a hall effect sensor that monitors if the bin lid is open or closed, an ultrasound sensor that measures the bin level, a temperature, and a humidity sensor. While the other group consisted of a few load sensors which detected the weight of the bin waste. These sensors are used for solid waste in order to keep track and manage waste collection for an optimized collection route and real-time detection of waste.

2.1.2. Bin Level Detection and Location of the bins

Bin level detection is one of the existing ways to manage waste. Determining the level can help in order to regulate waste and can benefit the garbage collectors by scheduling routes when the bin is full or reducing fuel expenditure by planning routes to go to the bin. Waste level detection can be done using several types of sensors. The following paragraphs give details about the type of sensor with example studies and smart bins used with the sensor.

Ultrasound and ultrasonic sensors are the most prominent sensors that can be used for level detection. These sensors are used for measuring the distance and time from one signal to go back and forth. It usually has mesh holes for transmitting sound and for a microphone. It has the capability of differentiating sounds from all types of objects-solid, liquid, or gas (Thota et al., 2018).

Determining the bin location is also important for different purposes such as computing the distance of the bins from each other, optimizing collecting routes, etc. Medvedev et al. (2015), mentioned that the use of sensors to detect bin location is efficient to know and plan the route of garbage collectors from destination to the waste bins. Sensors, when detecting the level of fullness of the bin, send signals to microprocessors or microcontrollers through Wi-Fi or other connectivity modules. These signals often indicate the precise location of the bins (Thota et al., 2018; Patel, Kulkarni & Sharma, 2019). Another added service once the location is determined is scheduling the collection of waste in a neighbourhood. Data gathered from sensors about the location of bins can be stored and processed to be used for future reports for waste collection and for mobile applications.

Tracking of bins can be done through Global Positioning System (GPS) which is a navigation system that can be used for applications such as traffic signal timing, weather forecast, earthquake monitoring among others. The receivers use necessary information such as the location of a moving vehicle through multiple ranges transmitted through signals to calculate the exact location of users or bins (Thota et al., 2018). Storing data in the main device is also another way to store locations. In a study by Sivasankari, A., & Priyavadana, V. (2016), a camera, which had a specific ID and location stored, was placed in each garbage bin. The cameras were used for live video streaming of the level of the bin. If the bin becomes full, the exact location of the bin is sent to the garbage disposal vehicles for collection.

2.2. OPEN DATA

2.2.1. Overview of Open Data

Open data can be defined as the publication and redistribution of scientific data without barriers in terms of permission and access. Data is supplemental for further studies, which is why reusing accessible data is necessary. Moreover, because the rate of scientific data discovery is increasing, accessibility of these data should increase as well (Murray-Rust, 2008).

Open data policies are published and improved by constant updating through different media. Data policies and transparency frameworks vary per country, as different countries choose what they want to publish for the citizens based on motivations and country authorities. Additionally, access also varies as licensing, the extent of data transparency, and privacy can become an issue. In a country, there are different governmental levels of data policy. An example of this is the Netherlands, where there are 3 levels such as national, ministerial, and the lower level of bureaucracy which are the research organizations under the ministries (Zuiderwijk & Janssen, 2014).

According to Stork (2000), the Open Data initiative is an Internet-based collaborative framework aimed at developing and innovating software such as intelligent reasoning systems, speech and handwriting recognition, recommendation applications, etcetera. The essential contributions of this initiative fall on three levels, as follows:

a. *domain experts* who help in learning fundamental algorithms
b. *infrastructure/tool developers* who retrieve necessary data and rewards netizens (i.e., people who regularly use the internet)
c. *non-expert netizens* who contribute over the web

Large datasets that are needed in some algorithms or systems to provide their services are often missing or not made accessible by private organizations or individuals. As an alternative, non-expert netizens can provide and contribute to the missing data. This collaboration amongst experts and non-experts is one of the reasons why there is growth in the participation level as well as a growing trend of this initiative.

The implementation of transparency of data in governmental websites has significantly increased in the past few years as some motivators are noticed and acknowledged by the said governments. The first motivator lies in the essence of freedom of information, which open data fulfils by becoming a path for the government to not have secrecy within their term and for the citizens. The European Commission and the implementers of The Open Government Directive in the United States believe that this will eventually strengthen democracy. The second motivator is in terms of economics. With data such as meteorological, geographical, macro, and micro statistics, road, traffic, and community information, and so on, being made public, there is a higher chance to inspire growth for the business and for the individuals.

2.2.2. Open Data and Plastic Waste Management

Examples of open data for creating solutions for smart cities can be found in places such as New York and Chicago, where combining multiple open mobility sources was used to infer the functional uses of their districts (Terroso-Saenz, Muñoz, & Arcas, 2021); Paris, where maps have been created on accommodation for the elderly and people with disabilities (Bonvalet & Ogg, 2008); and Zurich, where they have a 3D model of the city for easier municipal development planning and monitoring the urban climate in real-time, to name just a few (Neis & Zielstra, 2014; Schrotter& Hürzeler, 2020; Gessa & Sancha, 2020).

In a study by Latora et al. (n.d.), a combination of Geographical Information Systems (GIS) and demographic, territorial, and economic open data is generated in order to develop an efficient and sustainable waste-management policy in the province of Sicily (Italy). Likewise, a method to optimize the spatial tessellation of a geographical area for waste management is proposed (Richter et al. 2019). In particular, the system relies on several open data repositories to extract the shapefiles defining the administrative boundaries of the regions under study. Then, a framework is applied to such regions in order to define the best division so that each new area is managed independently.

The use of Open Data can also be essential in tracking the location of bins in a city. Layouts from the Geographical Information System (GIS) database about the location of the containers in streets and roads were used in a study by Bueno-Delgado, Romero-Gázquez, Jiménez, & Pavón-Mariño (2019). In a similar study by Shyam, Manvi, & Bharti (2017), the use of open data by using GIS data of the street segments of Pune, India was essential. A simulation for the bin placements was done with 5,000 waste bins considering 10 locations in the city. Another similar study by Zamorano et al. (2009) used GIS in order to determine the number of bin containers and their location in Granada, Spain. Two models were proposed to differentiate residential and commercial areas, while the parameters used in the model included distance among streets, number of inhabitants, and waste generation rate, among others.

Additionally, while GIS is a significant tool to use for analysing and displaying spatial data, it is not enough to do an analysis of municipal solid waste management system development through a scenario setting. A comprehensive simulation while changing spatial setting schemes is necessary to produce a spatial selection for bins using GIS (Shmelev & Powell, 2006). There are also certain times when sensor data can become voluminous. When this occurs, the data gathered, processed, and stored can be linked to big data. Open data is considered to be a backer of big data technologies including IoT and also the combination of both can be used for a broader vision for smart solutions (Misra, Das, Chakrabortty & Das, 2018).

2.3. MACHINE LEARNING

2.3.1. Machine Learning techniques in urban environments

It is possible to find in the literature a varied range of works that propose the use of Machine Learning techniques within urban environments for the provisioning of different services. For example, in a study by Liu et al. (2017), street images of Beijing were gathered from Baidu Map[1], and three machine learning models, that are different convolutional neural networks, were used to differentiate the street and building images from each other. These models were SIFT (Lowe, 1999), AlexNet (Krizhevsky, Sutskever, & Hinton, 2012), and GoogLeNet (Szegedy et al., 2015). After labelling these images, the building images were screened again to confirm the expert rating or the quality of the building for construction and maintenance. A similar study by Hecht, Herold, Meinel & Buchroithner (2013), used machine learning to automate the building and house classification of urban structures in Dresden, Germany through several data sources such as remote sensing images like satellite photos, and aerial photos and topographic data such as landscape models and maps. With these, Support Vector Machines (SVM) and Random Forest (RF) were both used as techniques in order to produce a full report on the urban structure type in the said city.

In another interesting study by Milusheva et al. (2021), the use of social media data such as Twitter data as a source to characterize different populations by their demographic or social media posts was explored as a resource for urban planning. Social media posts about road accidents and crashes were considered as events and were focused on the area of study, Kenya, which has road crashes as the number one cause of death in young adults. I Bayes and SVM were both used to analyze combinations of words such as "overturn" or "accident". After that, geolocation tags are then placed in order to identify the exact location or the area of the crash. To ensure these data are reliable, data quality and performance validation is conducted. A motorcycle delivery service is sent to the tagged location and the crash is verified.

2.3.2. Machine Learning techniques and Plastic Waste management

There are different techniques that can be applied to waste management planning through Machine Learning. As a matter of fact, there are Machine Learning approaches that were used in the modelling and prediction of the

[1] Baidu Map: https://map.baidu.com/

generation of the regional municipal solid waste management in Canada (Kannangara, Dua, Ahmadi, & Bensebaa, 2018). Artificial neural network (ANN) is a technique that is inspired by the human brain to learn and understand complex relationships when presented with data. When ANN was used in the study, it created better models than the decision tree as it showed 72% of accuracy in municipal solid waste generation models. The authors also explained the differences between using decision trees and ANN. While decision tree models are able to handle categorical variables, ANN has a high learning capacity which can model complex non-linear data as well. Some disadvantages of ANN, however, are that its inner architecture is difficult to interpret. Recurrent neural networks (RNN) also adopt a loop network in order to use previous information to provide a solution (Hussain et al., 2020). In terms of RNN, it was used in a system that enabled the long-term learning dependency of material identification in a mixed-waste bin.

In the city of New York, estimation of the weekly waste generation for the 609 administrative subsections of the 223 different sections of New York was decided and set through the comparison of neural network and gradient boosting regression tree (GBRT). GBRT is an advanced iteration of a normal decision tree which splits and weighs the data features through their errors to reduce the residual sum of squares (Kontokosta, Hong, Johnson & Starobin, 2018). In a study by Meza, Yepes, Rodrigo-Illari, & Cassiraga (2019), ANNs exhibited accuracy in the results of forecasts of the average generation rate of seasonal municipal waste in the city of Bogota (Colombia). It has higher accuracy and precision because of the nonlinear nature of the data. Decision trees were also used to reduce unpredictability in identifying patterns that are not known from the recognized patterns. SVMs were also utilized for the prediction of urban waste generation.

Another technique that helped with smart waste management was proposed by Gupta, Shree, Hiremath, & Rajendran (2019), where the shortest path spanning tree (SPST) was used to determine the shortest distance between bins that were mapped in the city. After that, genetic algorithms to optimize trash-collecting cycles, similar to the travelling salesman problem (Reinelt, 1991), were also used. It proved efficient in the optimization of the routes for the clearance of trash.

2.4. ICT SOLUTIONS FOR PLASTIC MANAGEMENT IN CITIES

The integration of Information and Communication Technology (ICT) solutions with urban development planning is one of the paramount points for the realization of smart cities. This growing technology can be used to improve the quality and efficiency of services in a city. Indeed, the concept of the Internet of Things (IoT) fosters the connection and transmission of data among any type of device in a city, allowing citizens and organizations to exchange these data and create collaborative services on top of these IoT systems.

A survey published by Anagnostopoulos et al. (2017) presented the different models of waste management opportunities in IoT-enabled smart cities. Thirty-six case studies involving different models which use different types of sensors such as capacity, weight, temperature, humidity, chemical, and pressure sensors were studied. The characterization and process of the survey were three-tiered; physical infrastructures, IoT technology, and software analytics. Physical infrastructure focuses on the waste bins, pipes, depots, dumpsites, types of waste, and other things that pertain to the hardware or physical properties that are associated with the bin and waste. IoT technology includes the recording and transferring of information through sensors, actuators, with the use of GPS, WSNs, RFID tags, and Near Field Communication (NFC) to measure the quantities of waste such as humidity, temperature, weight, capacity, and other attributes. Lastly, software analytics involves the analysis of data such as decision support systems, dynamic scheduling, dynamic routing among others.

In a study by Ramson et al. (2021), the proposed IoT waste management system used a bin level monitoring unit and a wireless access point unit. The level monitoring unit included an ultrasonic sensor, a network processor, and a power management unit. On the other hand, the wireless access point unit consisted of a wireless router deployed at several points close to the bins, to provide data connectivity to users. As it was self-powered due to its low dropout regulator, the entire unit could last up to 434 days based on the experiments. The unfilled levels could also be monitored precisely from a distance of 119 meters and less.

The study by Aleyadeh & Taha (2018) included the use of proximity and humidity sensors, load cells, a lever-activated switch, GPS and microcontroller. A mobile application was also used by garbage vehicle drivers to schedule bin collection and the location of the routes. In a similar study (Kumar, Shankar, Shah, Chinnu, & Venkataraman, 2013), Near Infrared Spectroscopy was used to classify five different types of plastics. Based on this technology, an automatic wireless sorting system was successfully created. The system includes an automated device that can detect 4 plastic items per second and can sort 5 different polymers through pattern recognition. The accuracy reported for sorting is at 96-98% for materials like polyvinyl chloride, polyethylene, polypropylene, polystyrene and 99% accuracy for polyethylene terephthalate. The monitoring of the system is done with a remote wireless interface.

Another IoT-based plastic waste management system (Aithal, 2021) includes ultrasonic sensors that can measure bin fill levels, RFID tags for easy tracking, load cells that can identify the weight of the bins, image sensors that capture the image of the bin from the inside, and temperature, humidity, and gas sensors, which are used for classifying the materials inside the bin. Each bin is also equipped with a bin controller, which transfers all the data to the server that can be accessed by the users and by garbage collectors. The database in the server contains and stores data such as the number of filled, empty and under-filled trash bins, bins that need immediate service, total weight of the bins, route information and communication status information of each bin.

In a study by Malche, Tiwari, Tharewal & Tiwari (2021), a waste collector that can use an application to retrieve information from the ultrasonic sensor attached to the bin, is proposed. Three different lights are used to notify the users about the fill level of the bins to know whether it needs to be cleaned or not. Yellow sign relates to the empty level, green for moderate, and red is being used for the full or critical level of the bin. It also shows the shortest path from the user to the garbage bin which shows the red light, or which means it needs cleaning. A similar study (Marwan et al., 2021) uses four different systems including a smart bin, control system, mobile phones, and a server. This study focuses mainly on the emptiness or fullness of the bin. The control system includes an ultrasonic sensor and an Arduino Uno processor.

Segregation, collection, and transportation are the purposes of a study by Lokuliyana, Jayakody, Dabarera, Ranaweera & Perera (2018). The types of waste bins are biodegradable, plastics, glass, and paper where each bin is equipped with an ultrasonic sensor that can detect fill level and hand movements to open the lid of the bin. The bin is also equipped with a Raspberry Pi Zero W development board that can automatically lock the bin lid when it is full. Text messages are also sent to the administrators of the system to notify them when the bin is full. With the data acquired through the different sensors, a calculation or algorithm was also developed to forecast the different types of garbage levels in the coming months for all types of waste.

In a study by Gade & Aithal (2021), different types of waste which need proper waste management were presented. Among the types include organic, hospital, electronic, nuclear, green, recyclable, and industrial waste. Although it was reiterated now that smart cities have grown exponentially, the waste management issues have also increased in terms of inefficacy and improper handling. The study suggests an in-depth analysis of the features that should be included in a smart waste management system such as waste bin fill status notifications, automated vehicles to collect waste, modernization of landfills, converting waste to energy, and waste collection vehicles running on natural gases. Smart bins include ultrasonic sensors to measure fill level, RFID tags to help with bin location tracking, load cell to determine the weight of the bins, image sensors to see the contents of the bin, temperature, and humidity sensor to detect industrial waste, and gas sensors for chemicals deposited in the bin. Additionally, the study suggests that waste collection vehicles are one of the most crucial parts of the smart waste management system. Some features that make an efficient vehicle include a robotic arm for the automation of collection, sites where solid and wet waste can be stored, accelerometer, air quality sensor, camera and wireless signals placed in the vehicles, and a GPS and real-time communication system with the server.

2.5. SUMMARY

As discussed in this chapter, in order to deal with an intelligent management of plastics, certain ICT technologies such as different types of sensors can be used. The different purposes of these sensors are in terms of segregation of trash, detection of bin level, and locating the bins in a particular place. Sensors such as accelerometers, or those aimed to measure temperature and humidity, are normally used for segregation waste by different types while ultrasound sensors are normally used for bin level detection. Open data also helps with the management of plastics through retrieval of the necessary open-sourced data such as demographic, territorial, economic, also national, ministerial, and scientific data from research facilities. These data are considered essential, especially when it comes to bin locations and distribution purposes. Machine Learning (ML) techniques were also discussed in this chapter. Some ML models were used to predict the generation of waste, and some were built on historical data about the disposal of waste to provide a solution aimed at the identification of waste.

ICT solutions can improve the quality and efficiency of services that can enhance the planning and development of a city. Another aspect that is focused on is connectivity, which allows citizens and organizations to exchange data in order to innovate and create more collaborative solutions and services. Many different services involve a combination of sensors, physical infrastructure, or IoT technologies. Some examples mentioned above include sensors connected to wireless systems monitored to create services for the citizens or the stakeholders. With these, services such as tracking of bin placements across a place, GPS situated in garbage trucks, or prediction of the generation of plastics can be done.

Different from the aforementioned studies, this thesis focuses on a holistic approach with the use of open data from countries that have municipal waste bins to infer the number of municipal bins in countries with limited to no bins. Additionally, weight sensors are attached in household bins to detect the bin levels for waste-pickers to be notified in order to pick up and dispose of in the municipal bins. Statistical analysis and machine learning techniques were also used in order to determine the number of municipal bins needed and to predict the shortest time for each waste picker to collect waste from households and until the municipal plastic waste bins.

III – DESIGNING A SMART BIN SYSTEM FOR ASSISTING THE MANAGEMENT OF HOUSEHOLD PLASTICS

III – Designing a Smart Bin System for Assisting the Management of Household Plastics

Exposure to plastic waste has been evidently increasing globally with almost every industry, corporation and community relying on plastics as they have become a commodity to the citizens. With the United Nations announcing plastic pollution as a global crisis, many countries have banned single-use plastics and started to urge people to help minimize their plastic usage. Furthermore, many manufacturers and producers have started changing their entire production industry to help in their own ways to reduce plastics (Schnurr et al., 2018; Borrelle et al., 2020). In this context, an efficient collection of plastic waste is being perceived as a fundamental public service as stated by Han & Ponce, 2015. The existing solutions and policies for plastic-waste management differ per country. However, most policies are strictly based on traditional waste collection methods with fixed schedules (Debrah, Diogo & Dinis, 2021). Intelligent techniques integrated into the prevailing system could be one of the solutions to make this collection more efficient. Some studies focus on the digitization of solid waste bin maps while trying to minimize the route length of the collecting vehicles. Additionally, current studies rely on the use of devices such as weight sensors to measure the bin levels of a municipality in real-time (Vijay et al., 2008; Catania & Ventura, 2014).

Despite these efforts, there are still situations in which due to no collection service, inadequate vehicle routing or insufficient funds, some communities find it difficult to have an accessible garbage collection. As stated by Abubakar, I. (2017), there are many cities in developing countries that are having issues with systematically and sufficiently providing garbage collection services. To worsen this situation, due to the COVID-19 pandemic, plastic pollution has visibly increased with the production of face masks, face shields and personal protective equipment (PPE) kits to protect against the transmission of the virus while lockdowns and quarantine restrictions are also applied in some countries (Sunjaya & Jenkins, 2020; Livingston, Desai & Berkwits, 2020).

As a result of these situations, we have identified a necessity for managing the increasing household plastic waste, especially for the elderly, disabled people, or people in a quarantine situation, who may find themselves in a difficulty in accessing the plastic-waste bins at the street. Thus, the aim of this work is to develop an intelligent collaborative system to predict the state of household plastic bins to optimize the route of residential garbage collectors or waste-pickers (Chen, Luo, Yang & Liu, 2018; Uddin, Gutberlet, Ramezani, Nasiruddin, 2020).

3.1. ARCHITECTURAL FRAMEWORK

Figure 4 depicts the first part of the process within the general architecture of the paper (Figure 2) in relation to the low-cost household sensors and the forecasting of the generation of household plastic waste. First, the system captures the current weight of the plastic-waste bins from a set of monitored houses by means of a scale sensor. Next, these weight data are sent to a back-end server. It comprises a dashboard to visualize all the collected sensor data. Moreover, it also includes a predictor module to forecast the future weights of all the monitored bins in the short term. Finally, such predictions are used to plan customized routes for the waste-pickers registered in the system so that they can collect the plastic waste at each monitored home proactively. To do so, both the location of the on-street plastic containers or dumps and the waste picker's means of transport are also considered to optimize the distances covered by these pickers.

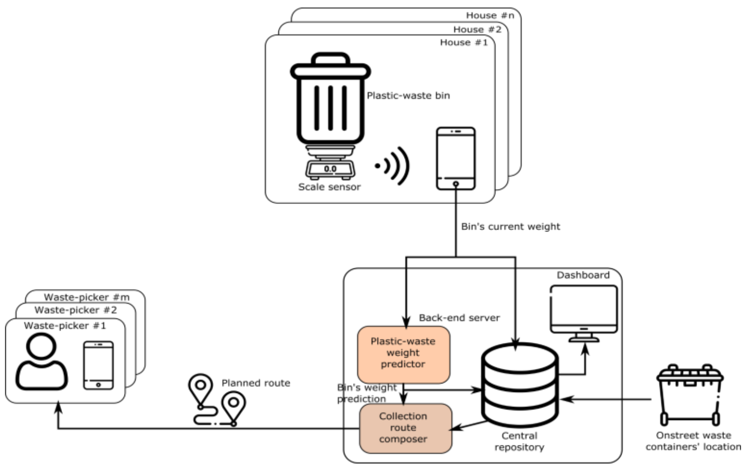


Figure 4: Smart-collaborative waste-management system.

3.2. SMART BIN

A plastic waste bin with the dimensions of 75 x 34 x 36 cm was used in this study (see Figure 5a). These dimensions allowed the placing of plastic waste of different sizes, forms, and weights into the bin. In this way, it was possible to use this bin in a large range of scenarios. The content of the bin is measured by means of a weight sensor (see Figure 5b). Since the plastic items placed inside the bin might have a very low weight, it was important to use an accurate sensor able to detect this kind of object in the container. For that reason, we opted for a coffee brew scale. This type of weighing scale has a very high sensitivity. In particular, we made use of the Acaia Pearl model (see Figure 6), an affordable weighing scale with a maximum capacity of 2000 g and a readability of 0.1 g[2]. Furthermore, it includes Bluetooth connectivity that allows real-time transferring of the bin's weight to a custom application installed in a mobile device[3].

(a)Bin used for the study

(b) Location of the weight sensor under the bin

Figure 5: Household plastic-waste collection

[2] Acaia Scale: https://acaia.co/collections/coffee-scales /products/pearl?variant=2433774125079

[3] Brewmaster application: acaia.co/pages/apps

Figure 6: Acaia Pearl weight sensor

3.3. DATA COLLECTION

Given the bin and the weight sensor described in the previous section, we undertook a palette of different experiments. These experiments were performed in the researchers' environment, which included their households and workplaces along with the people they were living with and their co-workers within the age group of 21-50 years old. Different types of households ranging from one to five persons in student housing, a workplace and a family house were explored (see Table 1). The researchers used these data to simulate the behaviour assessed with the target clusters, as explained in the next subsections. In each experiment, we put the weight sensor under the bin as shown in Figure 5b. Then, we connected the sensor via Bluetooth to a mobile device to collect the weight of the bin at each moment. Next, the bin was just used normally to put plastic waste in it. Thus, we performed several experiments involving different types and sizes of plastics such as plastic bottles, cans, plastic bricks and bags. Through these experiments, different behavioural clusters related to plastic-waste generation were extracted, as explained in subsection 5.1.4.

Table 1. Demographic characteristics of the participants in the experiment

Type of Household	Age Group	Gender	Num. Of Experiments
one-person	24-33	female	76
two-persons	49-55	male, female	26
five people	18-24	male	58
workplaces	24-38	male, female	16

Table 2. Data Samples collected from the experiments with the household bins

Date/Time	Total Time (sec)	Total Weight (g)	Weight Data
03/02/2021 20:12	2525	207.8	0.00;0.00;0.00;0.00;0.50;1.40;3.80;63.70;94.70;91.80;37.3;21.3;43.70;110.2;110.2;110.2;110.2;110.2;110.2;110.2;110.2;110.2;110.2;
02/02/2021 18:15	1013	112.5	0.00;0.00;0.00;0.00;0.00;0.00;0.00;0.00;0.00;0.00;0.00;0.70;0.70;2.20;76.90;76.90;76.90;76.90;76.90;76.90;101.90;101.90;101.90;101.90;101.90;101.90;101.90;

3.4. DATA CLEANING

Due to the high sensitivity of the scale sensor, it was able to capture any minimum weight fluctuation in the bin. Even though this allowed us to perceive any plastic item placed into the bin, a side effect was that this also generated rather noisy data sequences. As a result, a data curation process was performed over the collected data. The goal was to keep only the actual and meaningful weight variations of the bin.

To do so, each experiment was regarded as a time series. This allowed us to seasonally decompose each series and therefore keep its *trend* dimension by discarding its *residual* and *seasonal* parts. The rationale for this decision was based on that the trend dimension actually captured most of the meaningful weight changes of the bin during each experiment.

3.5. DATA CLUSTERING

Once the sensor data were smoothed, it was possible to group them to represent different behavioural patterns related to plastic-waste generation in households. To do so, we first extracted five different features from each experiment's time series, namely:

- The mean weight of the bin contents throughout the experiments. (*m)*
- The value of the first quantile of the bin contents during the experiments. (*q25)*
- The value of the third quantile of the bin contents during the experiments (*q75*)
- The number of usages of the bin during the experiment, i.e., the number of times the user puts one or more items in the bin (*u)*
- The number of items that the user actually places into the bin. This is calculated as an estimation based on the assumption that an average item weighs around 10g. (*i)*

Note that adding the quantile-based variables *(q25, q75*) might cause multicollinearity with respect to the mean weight variable *m*. However, both features have been included as part of the clustering step to provide a more descriptive representation of each cluster. This verbose representation makes it easier to link each cluster's centroid to a particular user profile as it will be described in subsection 5.1.4.

The clustering algorithm *K-means* was fed with these features to uncover different latent patterns in the experiments. Thus, each cluster was regarded as a different user profile within the system's contextual operation (Yu et al., 2018).

3.6. WEB APPLICATION

One of the contributions of this work is the development of a web application that enables a continuous data visualization of the weight data for the plastic waste in the smart bin (see the dashboard component in Figure 4. This application also includes a module for predicting the generation of plastic waste in the smart bin (see subsection 3.7.)

The development of this application has followed the SCRUM methodology. This methodology divides the application development into small stages, known as *sprints*, which offer a high degree of adaptation and flexibility and customer testing before finalizing the development. The SCRUM team was led by the Product Owner, a role that corresponded to Andrés Muñoz, who stated the requirements of the applications as *user stories*. Fernando Terroso-Sáenz acted as the SCRUM Master, ensuring that the SCRUM practices and principles were followed in the project. Finally, the Development Team consisted of Navjot Sidhu and Alberto Pons-Buttazzo, who created and maintained the software. For this development, 8 sprints, 7 user stories, 28 tasks and 390 h were needed, resulting in an average of 14 h for each task.

For the web application, PHP was used for the back end, whereas the front end was developed with HTML, Bootstrap, and the JavaScript language. Bootstrap is a library for web applications that offer multiple tools to easily customize a website with free templates, a responsive design and maintaining browser compatibility. In addition, the following software tools were used: phpMyAdmin (MySQL administration), Visual Studio Code (source code editor), and XAMPP to manage the Apache web server and the database. The Python programming language was used for the predictor module.

3.7. WEIGHT PREDICTION METHOD

Another key feature of the proposed system is the prediction of the weight of the plastic waste in each bin (see Figure 4). The three-step procedure applied to this end is explained next.

First, we identify the meaningful variations in the weight of the bin through an online analysis of the measurements from the scale. In brief, each new measurement w_i reported by the scale at a time instant t_i is considered a meaningful weight variation (MWV) w_i^m if the following three conditions are fulfilled:

1. w_i- $w_j^m \geq \Delta_m, j < i$
2. t_i- $t_j \geq \Delta_t, j < i$
3. $w_i \geq w_{i+1}$

The first condition ensures that the difference between a new value w_i and the most recent MWV w_j^m is actually meaningful. The second one ensures that the time difference between such a previous w_j^m and the new value is larger than a certain threshold Δ_t. Please note that a time instant *t* in this setting refers to the time in seconds after the experiment under consideration began. The third condition ensures that the following weight value w_{i+1} does not indicate a higher value than the current one, and therefore w_i can be considered a MWV w_i^m. It should be noted that all the measurements come from the smooth version of the data collected from the weight sensor according to the data cleaning stage described in subsection 3.3.4.

In the second step, each new meaningful variation w_i^m is stored in a set W. This set comprises all the meaningful weight changes in the bin detected so far in an experiment. It is used to feed a linear regression model whose goal is to predict the weight of the bin given a future time instant t,w_t, expressed as

$$w_t = \beta_0 + \beta_1 \times t \qquad \text{(a)}$$

Note that this model is re-trained each time W is enlarged with a new measurement.

In the third and final step, the linear regression model is used to estimate how long it will take to fill the bin. Assuming that the maximum weight of the bin is defined by w_{max} ,such a time instant t_{max} can be estimated from the original model as

$$\hat{t}_{max} = \frac{w_{max} - \beta_0}{\beta_1} \qquad \text{(b)}$$

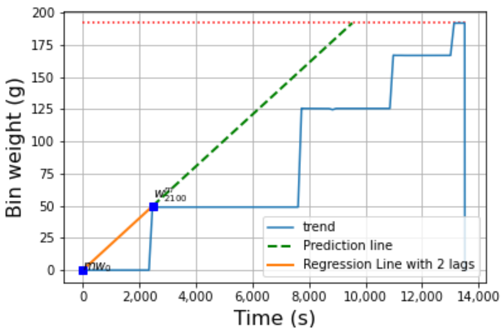
Therefore, the time horizon to fill, the bin will eventually be $\hat{t}_{max}$- t_{now} where t_{now} is the current time instant.

All in all, this approach defines a particular regression model for each experiment. In that sense, the complexity of the adopted model is quite low, as it takes the form of a univariate linear regression. This will ease the actual scalability of the proposal by instantiating numerous ad-hoc models without requiring an expensive computational infrastructure.

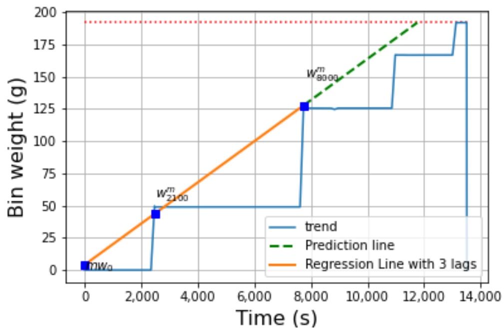
For the sake of clarity, Figure 7 depicts an illustrative example of the aforementioned mechanism given three different time instants of a particular experiment. In the first moment (Figure 7a), two different MWVs have been identified at timestamps 0 and 2100. Therefore, the set W comprises such variations m_0 and m_{2100} giving rise to a regression line whose projection is depicted as a dotted green line. As it can be observed, this projection line reaches the w_{max}value (horizontal dotted red line in Figure 7a) at a time instant rather far to the actual one, giving rise to a quite large prediction error (~5000s).

After that, a new MWV is detected at time instant 8000 which gives rise to a new linear-regression line based on the new set$W$(Figure 7b). With this new point, the regression line approximates better to the filling instant as its projection reaches the maximum weight closer to the actual time instant with an error below 2000 s. Finally, a fourth MWV (mv_{1100}) is added to compose a new regression line (Figure 7c). Again, it can be seen that the new projection can predict the filling instant even better than the other two regression lines with an error below 1000s. Unsurprisingly, adding more MWVs to the model improves its prediction capabilities.

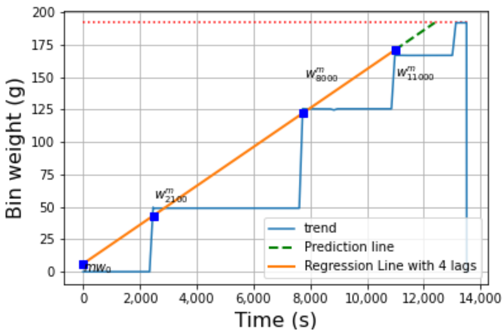
It is worth mentioning that changing the order of the items when they are introduced in the bin might slightly affect the accuracy of the predictor. However, the weight range of the plastic items that are introduced in the bin is quite limited because, for example, the weight difference between a small plastic bottle and a big one is within the range of a few grams. Consequently, the MWVs that give rise to the regression line usually involve similar weight increments. As a result, the order in which such increments occur does not meaningfully change the actual slope of the regression line and its associated prediction. Figure 8d shows the prediction of the model when the same plastic items are introduced in the bin in reverse order. As observed, the projection of the regression line reaches the w_{max} level with a similar error to the one obtained with the original order.



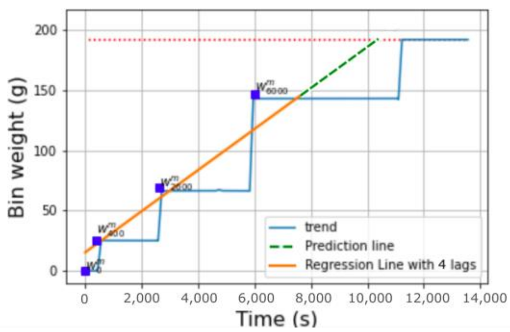
(a)Regression line when two MWVs are detected



(b)Regression line when three MWVs are detected



(c) Regression line when four MWVs are detected



(d) Prediction with four MWVs when the same items are introduced in reverse order in the bin

Figure 7: Example of the prediction mechanism for an experiment. The blue squares represent MWVs. The horizontal dotted red line indicates the maximum weight of the bin.

3.8. COMPOSITION OF THE ROUTES FOR WASTE-PICKERS

The weight predictions described above feed the module in charge of composing the routes for the set of registered waste-pickers (WP) (see Figure 4). This module executes the following approach to create the set of routes for these waste-pickers. First, each waste-picker $wp \in$ WP is required to indicate the hours of the day $H_{wp} = < h_{wp}^{min}, h_{wp}^{max} >$ that he/she is available to perform a collection route. Next, every day at the beginning of each time range H_{wp}, the system collects the set of pick-up points to be covered $P =< p_1, p_2, \ldots, p_N >$ where N is the total number of bins under control. Each pick-up point p_1 is defined by a tuple $(l_i, \hat{t}_{max,i})$ where l_i is the location of the house for the i-th bin and $\hat{t}_{max,i}$ is the estimated filling hour returned by its associated predictor (subsection 3.3.7.).

Therefore, the definition of a personal collection route for a waste-picker $wp \in$ WP can be formulated as the following problem:

Given a set of pickup points P and an hour range H_{wp}, Find an ordered sequence $S_{wp} =< (p^1, h^1) \rightarrow (p^2, h^2) \rightarrow \ldots \rightarrow (p^5, h^5) >$ where each tuple (p^1, h^1) indicates that the pickup point $p^i \in P$ should be visited at the h^j hour of the day $(h^j < h^k, \forall k > j)$.

To obtain a set of suitable sequences, the following restrictions must apply in the generation process:

1. $\boldsymbol{h^1 \geq h_{wp}^{min}}$ and $\boldsymbol{h^5 \leq h_{wp}^{max}}$;and
2. $\forall(\boldsymbol{p^j}, \boldsymbol{h^j}), \boldsymbol{h^j} \leq \hat{t}_{max,j}, j \in [1, s]$

The first condition ensures that the time duration of the calculated route fits into the hour range defined by the waste-picker. The second one ensures that the waste picker will collect the plastic waste at the j-th point of the sequence before its estimated filling hour $\hat{t}_{max,j}$. It is worth mentioning that the set of pick-up points not included in a route $\boldsymbol{S_{wp}}$ gives rise to a new set P' of pick-up points. This new set will be used to compose the route of other waste-pickers by following the same approach. This process is repeated until no waste-pickers are left or all the bins are covered.

To conclude, note that this problem fits into the category of *vehicle routing problems with time windows*. Thus, we have used the ILOG solver, a well-known constrained programming system, to generate the collection routes of the waste-pickers by considering the definitions and restrictions described above. In brief, this algorithm follows a tree-based search on the solution space to find routes that accomplish all the listed restrictions (Li, et al., 2020; Shaw, Furnon, & De Backer, 2003). The results of the above-mentioned proposed system are described in Section 5.

IV - URBAN PLASTIC WASTE PLANNING APPROACH: A CASE STUDY FOR INDIA AND THE PHILIPPINES

IV - URBAN PLASTIC WASTE PLANNING APPROACH: A CASE STUDY FOR INDIA AND THE PHILIPPINES

With the sheer number of plastics in use around the world today, and with enough knowledge about how they affect our environment, in-depth population awareness of the different types of plastics and how they must be disposed of is needed (Medvedev et al., 2015). Accumulation of plastics and the strategies for their disposal vary due to several factors, such as cultural norms and types of urban settlements (e.g., small cities vs. megalopolis). According to Sivaramanam (2016), it is paramount to elaborate strategies to properly manage plastic waste in cities, Polyethylene Terephthalate (PET) being the most dangerous type of plastic to control. PET plastic is commonly used for water bottles, oil containers, cosmetics, projector films or balloons, among others. This type of plastic is one-time use only because of the toxic chemicals that could come out when exposed to solar heat, and therefore they should be placed in the proper containers for their management.

While this type of plastic waste is usually controlled in developed countries by means of efficient distribution of specific bins and recycling strategies, it is not the case for some Eastern countries such as India and the Philippines (Ferronato & Torretta, 2019; Di Maria, Lovat, & Caniato, 2017). One example is Quezon City in the Philippines, where the Payatas dumpsite, one of the largest former dumpsites in the country, is located (see Figure 8(a)). To the best of our knowledge, there is no official implemented policies to control and reduce plastic waste in the entire country yet[4]. Regarding India, there are two states which show completely opposite strategies. The first one is Punjab, where there is no management of plastic waste. Here, the local government provides a piece of land to each house to be their personal dumpsite. These dumpsites are in the open containing mixed waste and no official organization is responsible for collecting them. They wait for 3-5 years to let it decompose and then they use the waste as fertilizers for the farm, and the remaining as a substitute for wood to make fire (see Figure 8(b)). The other state is Gujarat, which has complete support from the government to segregate waste. Indeed, a project is currently underway to test a waste management policy until

[4] Department of Environment and Natural Resources: https://faspselib.denr.gov.ph/taxonomy/term/1699 accessed on: May 8, 2021

2023, showing that a real interest in controlling plastic waste is emerging in this country[5].

Figure 8: (a) Payatas Dumpsite; (b) Open dumpsite in Dhaner, India

An alternative to tackle the plastic waste problem in these cities is to design customized urban planning for managing plastic waste in each target city based on efficient strategies already implemented in some Western cities. To do this, our proposal is to rely on the use of open data related to the plastic management available from such Western cities along with other relevant data such as population density, venue distribution and even shape of the cities regarding the distribution of the streets. The Open Data movement in smart cities fosters the collection and sharing of data amongst individuals, industries, and countries (Ahlgren, Hidell & Ngai, 2016). Thus, the use of open data in this work is included in the *third data revolution* for urban planning in the smart city framework as defined elsewhere (Kourtit, Elmlund, & Nijkamp, 2020), which allows the use, re-use and distribution of data without legal, social or technological restrictions.

This chapter explains the retrieval of open data in order to statistically analyze the distribution and placement of municipal plastic waste bins in a city. As figure 9 shows, the urban features of four specific Western cities related to plastic management (namely New York (USA), Stavanger (Norway), Madrid and Malaga (Spain)) were explored where results are applied to three different city areas suffering from dumpsite problems in the two aforementioned countries, namely India and the Philippines. Through statistical methods in mapping the target and reference cities, this urban planning method may help develop countries to devise a custom-built, low-cost strategy to deal with plastic waste management by adapting successful experiences in other countries (See Figure 9).

[5] Swachh Bharat India: https://swachhindia.ndtv.com/category/environment/ Accessed on May 8, 2021

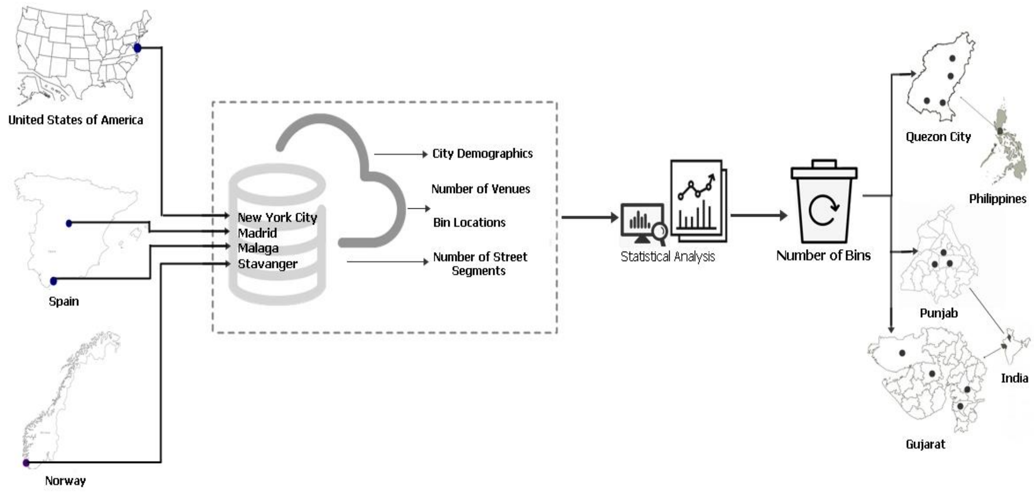


Figure 9: Urban Planning overview

4.1. DESCRIPTION OF THE REFERENCE CITIES

In order to define a bin allocation policy for the target urban areas in the Eastern countries of this study, we have used as a reference several socio-economic factors from four different cities, namely New York, Madrid, Malaga, and Stavanger. The locations of these four cities are shown in Figure 10. There are several reasons for the selection of these cities as reference ones. In that sense, they offer a rich ecosystem of open-data platforms to extract different features of their urban life. Moreover, they have different demographic profiles, urban topologies and social life as explained in the following subsections. This heterogeneity of the reference cities is pursued to avoid potential overfitting of the proposal towards a particular type of urban topology. Next, the stages for the data extraction for each city are described.

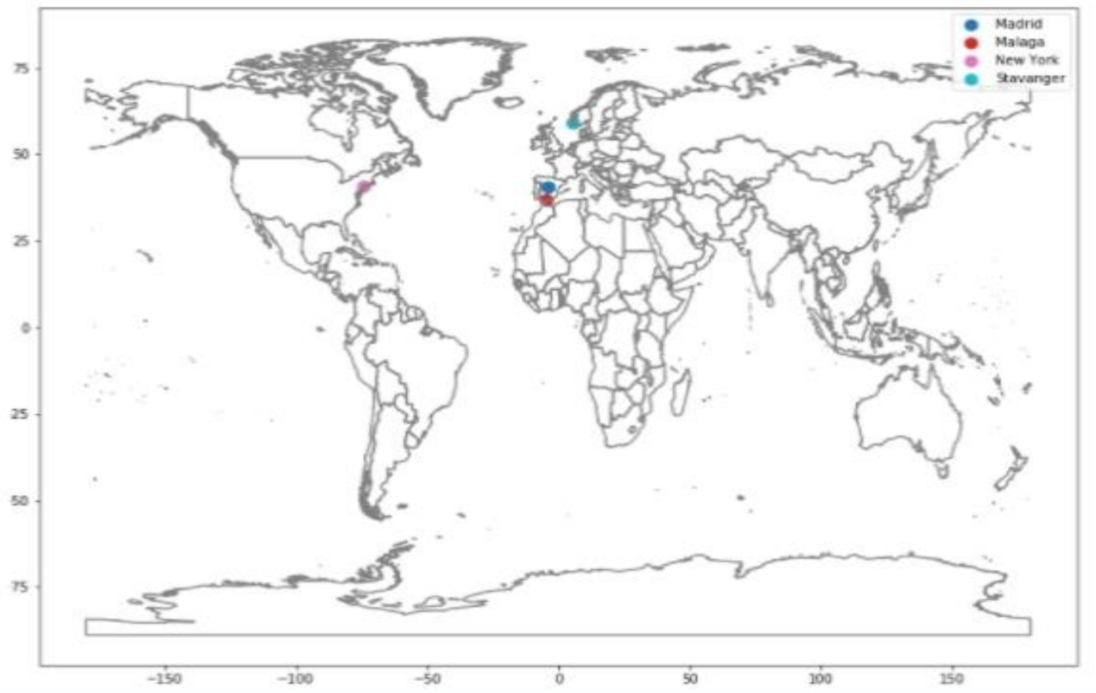


Figure 10: Location of the four reference cities

4.1.1. Extracted urban contextual data

For each reference city, we have taken into account four different dimensions that might have an impact in the amount of plastics generated in a particular urban area:

- First, the demographics of each city and its distribution per each of its districts. This feature allows estimating the volume of *stationary* human presence in each of the areas of the cities.
- Secondly, the number of venues covering different categories in each city and their distribution per district. In this case, the venue distribution allows capturing the underlying types of human activities.
- Third, the number of street segments in each city district. This data is a latent feature of the underlying urban topology of the districts. Such a topology may be a quite relevant feature for the definition of a proper bin allocation policy. Indeed, districts with different numbers of street segments would probably have different patterns of human movement and, thus, very different activity behaviours. In that sense, a region with many

recreational areas and big building blocks would comprise less street segments than a residential area composed of single-family homes and, hence, both regions might have completely different patterns of waste generation.

- Finally, we have also collected the location of the bins in each of these cities. This allows us to calculate statistics such as the total number of bins and the average distance among pairs of bins in each district of the four cities.

At this point, we should clarify that both the venues and the number of streets features of the four cities have been collected from the public spatial repository OpenStreetMap (OSM) platform[6]. The other two features, namely the demographics and the bins' locations, have been accessed through the corresponding open-data portals of each of the cities. Table 3 summarizes the urban dimensions extracted from each reference city and their associated sources.

Table 3. Contextual features extracted for each reference city and its associate data source.

Urban contextual features	**Data source**
City demographics (CD)	City's Open Data portal
Number and type of venues (NV)	OSM
Number of street segments (NSG)	OSM
Bins location (BL)	City's Open Data portal

More in detail, the NV and NSG data have been extracted from OSM by considering the spatial polygons that define the geographical area of each city stored in the OSM repository. Then, the venues (defined as point-based spatial objects) and street segments (defined as line-based spatial objects) that spatially fit into such polygons are retrieved from the platform. For that goal, we make use of the Overpass Application Programming Interface (API)[7]. This is a built-in interface provided by OSM to easily and programmatically retrieve spatial objects from its repository.

[6] Open Street Map: OpenStreetMap

[7] https://wiki.openstreetmap.org/wiki/Overpass_API

4.1.2. New York City, U.S.A.

The first reference city is New York City (NYC), in the United States of America. This city has five boroughs, namely Manhattan, Brooklyn, the Bronx, Queens, and Staten Island.

According to Table 4, all the NYC districts but Staten Island comprise very large populations above 2 million people. In terms of population density, Manhattan is the densest one with more than 52,000 people per km^2. Besides, it is possible to observe meaningful differences in the distribution of bins in each district. More in detail, Queens exhibits a much less dense distribution of bins as its average pairwise distance between bins is 8.63 km. This is a much larger distance than the ones observed in the other four districts, with distances ranging from 4 to 6 km.

Table 4: Overview of the demographics and number of bins in New York City.

NEW YORK	Population	Area (km^2)	Population Density	Number of bins	Average distance of bins (km)	Num. of street segments
Bronx	2,717,758	110	24,707	108	4.78	17,338
Manhattan	3,123,068	59.1	52,844	184	5.82	9,702
Queens	4,460,101	280	15,929	117	8.63	55,192
Brooklyn	4,970,026	180	27,611	94	6.35	22,709
Staten Island	912,458	152	6,003	42	6.71	16,060
Sources	NYC OpenData Portal (NYC OpenData, n.d, NYC OpenData, n.d-2), OpenStreetMap (Openstreetmap. (n.d.))					

Regarding the venue's data, Figure 11 shows its distribution in NYC. As observed, a high percentage of venues are restaurants, followed by places of worship and parks areas. All of them are above the 10% of the total venues of the cities. This indicates that NYC has a quite important catering sector. This is an important detail as this economic sector might be an important factor in the total generation of plastics within the city. A report by the Department of Environmental Conservation mentioned that 20% of waste generation (the second highest in terms of waste generation) came from restaurants and the catering industry ("Waste generation in New York City and the State of New York", n.d.).

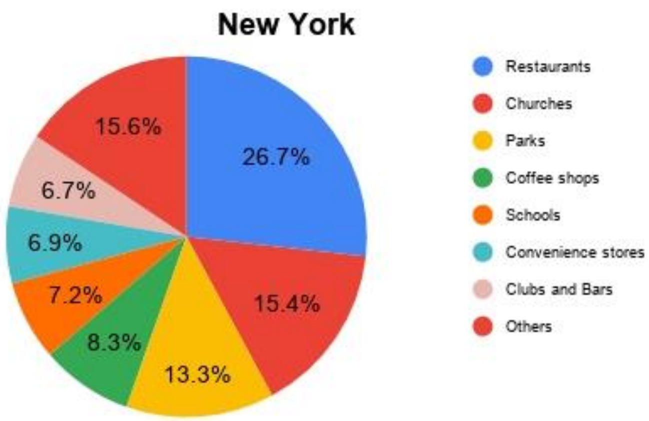


Figure 11: Number of establishments in terms of percentage in NYC

Finally, the number of streets is depicted in Figure 12. It is important to note that this figure indicates the number of street segments in each district. In that sense, a street might be split into different segments if it is crossed, for example, by other streets. Thus, Queens is the district with the densest network with 124,001 street segments. This is a volume of segments much larger than in other districts like Queens (55,192 streets), Brooklyn (22,709), The Bronx (17,338) or Staten Island (16,060). Finally, the Manhattan district is the only one comprising less than 10,000 roads. Unsurprisingly, there is a strong correlation between the total geographical area of a district and its total number of streets.

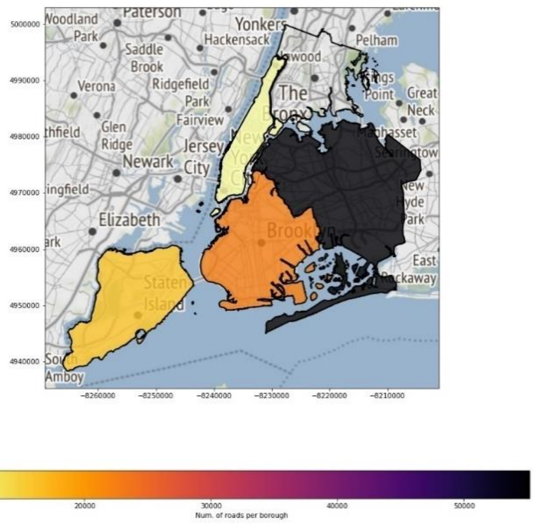


Figure 12: Distribution of number of streets in each of the five NYC boroughs.

4.1.3. Madrid, Spain

The second reference city is Madrid, the capital of Spain. It has a total of 21 districts, and this study focuses on only 9 representing the downtown, namely Salamanca, Chamartin, Moratalaza, Ciudad-Lineal, Hortaleza, Vicalvaro, San Blas-Canillejas, Barajas and Retiro.

Table 5: Overview of the demographics and number of bins in Madrid.

MADRID	Population	Area (km^2)	Population Density	Number of bins	Average distance of bins (km)	Num. of street segments
Salamanca	145344	5.41	26,865	736	1.22	2,050
Chamartín	141527	9.19	15,400	1095	1.83	2,935
Moratalaz	92958	6.34	14,662	1933	1.08	1,728
Ciudad-Lineal	212565	11.36	18,711	2258	2.02	4,201
Hortaleza	185738	28	6,633	2838	1.9	7,294
Vicálvaro	72213	32.7	2,208	1547	1.32	3,498
San Blas-Canillejas	155825	21.81	7,144	2218	2.12	4,545
Barajas	48315	42.66	1,132	1003	1.21	4,478
Retiro	118252	5.37	22,020	495	1.13	2,493
Sources	Madrid city council website (n.d.), Madrid Open Data Portal (n.d.), OpenStreetMap (Openstreetmap. (n.d.))					

Table 5 shows the different population with Ciudad-Lineal as the city with the highest population. The densest district with 26,865 people per km^2 is Salamanca. As the district with the highest population, Ciudad-Lineal also has the highest number of bins, with an average distance between the bins at 2.02 km^2. The other districts namely San Blas-Canillejas and Moratalaza also have a significantly high amount of bins, while the district with the lowest amount of bins is Retiro even though it has a population of more than 100,000.

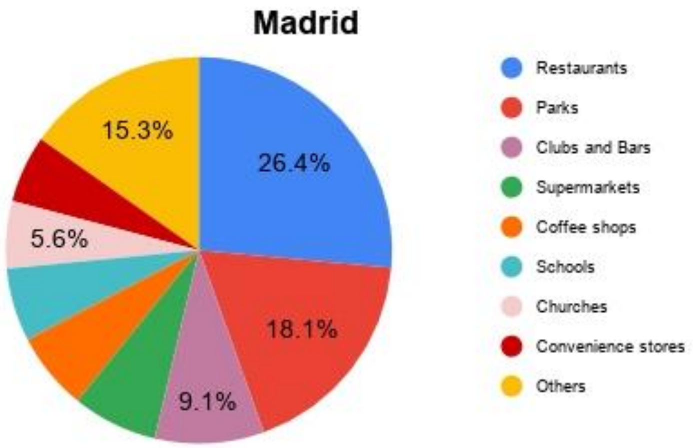


Figure 13: Number of establishments in terms of percentage in Madrid

Additionally, Figure 13 shows the percentage of different venues in Madrid. The highest number of venues are restaurants followed by parks and others, which consist of museums, libraries, and gas stations, among others. This stipulates that, like New York City, Madrid too, has a large percentage belonging to the catering sector. Indeed, from 2010 to 2018, municipal waste generated in Madrid ranged from 20,000 to 23,000 tons (“Eurostat Report Spain”, n.d.). It was also reported that 21.8 kilogram per capita of plastic waste was effectively recycled in 2017.

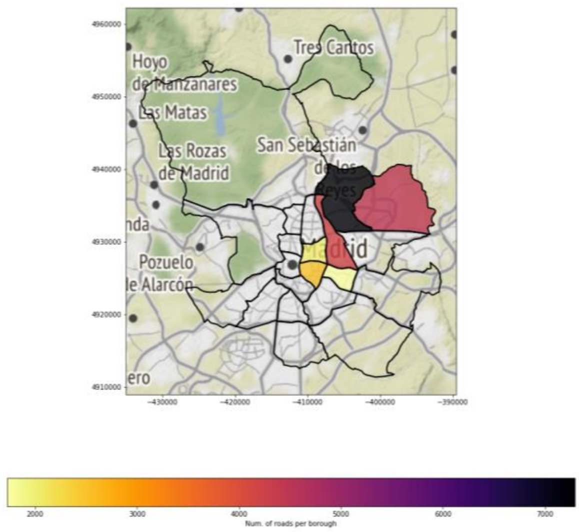


Figure 14: Distribution of the number of streets in Madrid

Lastly, in the 9 districts, the total number of street segments are 33,222 as is shown in Figure 14. Hortaleza has the most roads with 7,294, followed by San Blas-Canillejas with 4,545 and Barajas with 4,478. The number of streets can show a significant relation to the area, or population of the district. But in the case of Madrid, Ciudad-Lineal, which has the highest population, has the fourth-highest number of street segments, while Barajas, which has the largest area, has the least number of streets.

4.1.4. Malaga, Spain

The third reference city is Malaga, located in the Andalucía region of Southern Spain. This city has 11 districts, as listed in Table 6. As shown in this table, the district *Carretera de Cadiz* has the highest population and is the only district with over 100,000 people. It is also the densest district with 20,254 people per km^2, while *Este* is the district with the largest area (126 km^2) in the entire city. *Churriana* is the district with the greatest number of bins with an average distance of bins at 3.96 kms.

Table 6: Overview of the demographics and number of bins in Malaga.

MÁLAGA	Population	Area (km^2)	Population Density	Number of bins	Average distance of bins (km)	Num. of street segments
Centro	84,988	5.87	14,478	20	0.36	3,502
Este	67,289	126.63	531	285	3.42	2,860
Ciudad Jardin	37,769	76.21	495	2	0.07	2,693
Bailen-Miraflores	62,834	6.39	9,066	31	0.51	1,429
Palma-Palmilla	29,862	25.37	1,177	6	0.33	967
Cruz de Humilladero	93,955	9.91	9,480	142	1.81	3,383
Carretera de Cádiz	113,424	5.6	20,254	265	2.62	3,743
Churriana	20,449	37.32	547	409	3.97	3,223
Campanillas	17,472	59.77	292	202	1.03	1,335
Puerto de la Torre	49,442	42.26	1,169	233	1.14	1,556
Teatinos-Universidad	34,405	-	-	100	2.43	2,191
Sources	City Population Website (2020), Malaga Open data Portal (n.d.), OpenStreetMap (Openstreetmap. (n.d.))					

Figure 15 shows the distribution of venues in the city of Malaga. The highest percentage are other venues which consist of sports centres, clubs and bars, government offices, hotels, convenience stores, etc. They are followed by restaurants and schools. This shows that, unlike NYC and Madrid, the catering and education sector are almost equally important even though the other establishments are higher in total collectively. Indeed, in 2018, with a total of 301,000 tons of waste collected in Malaga city, 8,700 tons were plastic waste ("Waste collection in Malaga", 2013). Although catering is an evident industry that generates tons of waste, the education industry should not be disregarded when it comes to plastic waste generation, as it is also shown elsewhere (Smyth, Fredeen, & Booth, 2010).

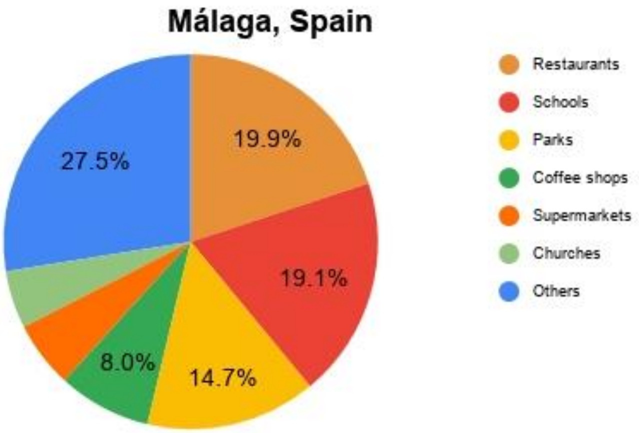


Figure 15: Number of establishments in terms of percentage in Malaga

Regarding the number of streets, as shown in Figure 16, Malaga has a total of 26,882 roads with the district of Carretera de Cadiz with 3,743 roads, Centro with 3,502, Cruz de Humilladero with 3,383, Churriana with 3,223 and the other districts, Bailen Miraflores, Campanillas, Ciudad Jardin, Este, Palma-Palmilla, Puerto de la Torre and Teatinos Universidad with less than 3,000 roads.

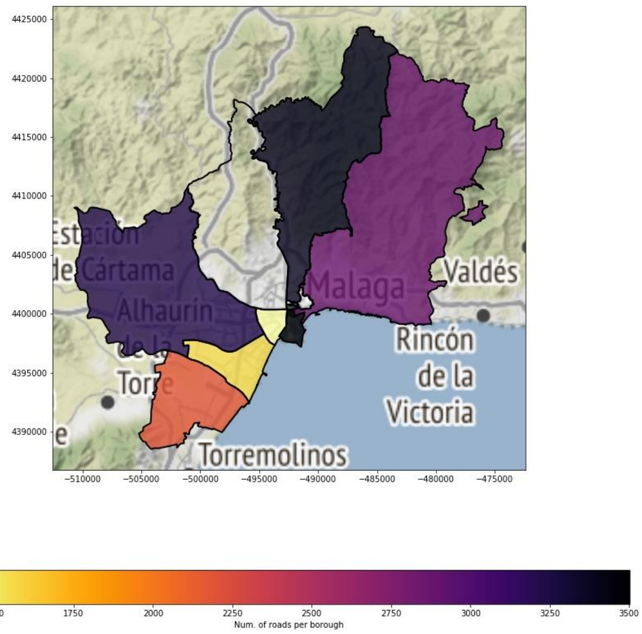


Figure 16: Distribution of the number of streets in Malaga

4.1.5. Stavanger, Norway

The fourth and last reference city is Stavanger located in the Southwestern part of Norway. This city has 6 districts which are listed in Table 7. Almost all the districts, except for Rennesoy, have a population of over 10,000. Not only does the district of Eiganes og Valand have the highest population of 23,616, but also it is the densest one with 3,368 people per km^2. Furthermore, even though Rennesoy has the lowest population, it is the district with the largest area in Stavanger. Hillevag, a district with 19,681 people and an area of 8.08 km^2 has the most number of bins with an average distance of 1.45, between the bins.

Table 7: Overview of the demographics and number of bins in Stavanger.

STAVANGER	Population	Area (km^2)	Population Density	Number of bins	Average distance of bins (km)	Num. of street segments
Madla	21,236	13.87	1,530.90	136	2.35	2,118
Hundvåg	13,217	6.41	2,061.90	74	1.40	2,026
Hillevåg	19,681	8.08	2,435.70	212	1.45	3,892
Storhaug	16,544	6.43	2,571.90	188	0.86	1,793
Hinna	22,581	15	1,505.40	187	1.65	777
Eiganes og Våland	23,616	7.01	3,368.90	181	1.39	3,443
Tasta	15,319	10.87	1,409.20	98	0.74	1,943
Rennesøy	4,755	65.51	72.58	27	3.12	38
Sources	City Population Website (n.d.), Stavanger Open Data portal (n.d.), OpenStreetMap (Openstreetmap. (n.d.))					

Figure 17 shows the distribution of venues which indicates that the highest percentage of venues are parks, followed by other venues such as gas stations, museums, government offices, convenience stores, shopping centres and hotels, among others, and restaurants. This indicates that the generation of plastic waste might be from these venues as these are established more in the city. In one of the main waste facilities in Stavanger in 2019, it was noted the arrival of waste from households, parks, shopping centres, offices and other stores containing 15,973 tons of plastics out of 66,250 total tons of waste (Ivar Iks, n.d.). Finally, as shown in Figure 18, Stavanger has a total of 15,992 streets. The rest of the districts have less than 3,000 streets.

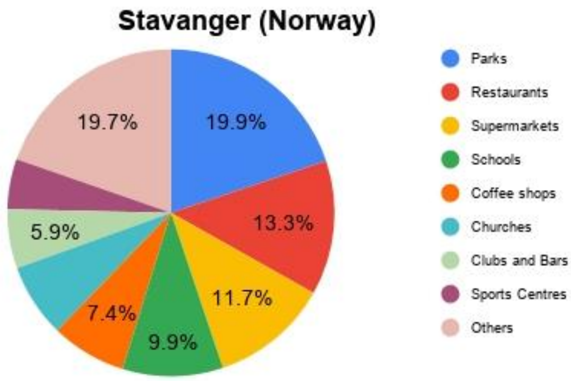


Figure 17: Number of establishments in terms of percentage in Stavanger

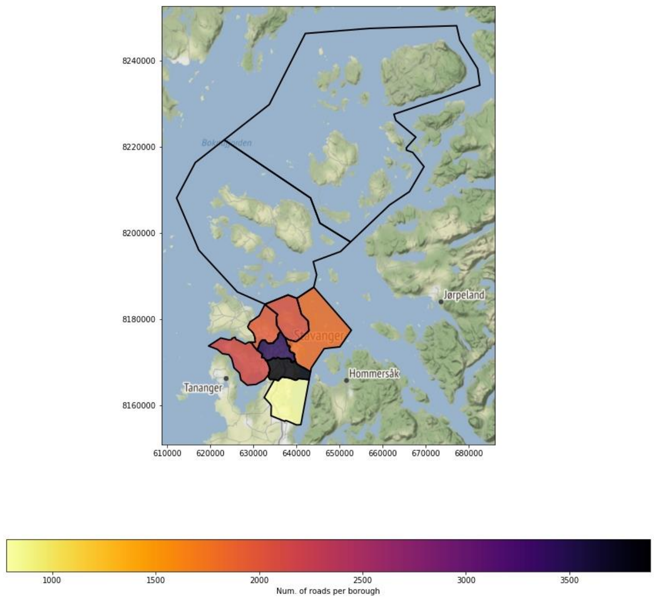


Figure 18: Distribution of the number of streets in Stavanger

4.1.6. Selection criteria for the reference cities

Bearing in mind the extracted urban features, it can be seen that the four reference cities actually reflect different urban scenarios. To start with, they cover quite different population densities, ranging from roughly 300 in Malaga to more than 52,000 people per km^2 in New York City. In terms of geographical size, there is also a large variation of the target neighbourhoods with quite small ones like Salamanca in Madrid (5.41 km^2) to much wider ones like Manhattan in New York City (52,844 km^2).

Furthermore, clear differences in the distribution of bins are found between the European cities and the American ones, since New York City has a sparser distribution with distances among bins above 5 km than the other three cities with distances below 4 km in all the cases.

Finally, the latent human activity reflected in the distribution of venues also suggests some remarkable differences among the selected cities. Whilst Madrid, New York City and Malaga seem to have quite an active nightlife with many different venues related to restaurants, coffee shops and nightclubs, Stavanger seems to be a more family-friendly environment where parks and supermarkets are much more relevant.

4.2. DESCRIPTION OF THE TARGET CITIES

This section describes the target areas of the developing countries, namely the Philippines and India, where we apply our method to estimate the number of plastic recycling bins. These areas are selected based on their different urban features with respect to the size of the areas, population density and venue distribution, as explained below.

4.2.1. Quezon City, Philippines

For many years, the Philippines has been a centre of natural disasters such as floods due to the blockage of drainage because of plastic waste. According to Atienza,V. (2020), the Philippines produce approximately 2.7 million metric tonnes of waste each year, as of June 2020. Not only do they handle the waste people of the Philippines produce, but also for many years, it has been reported that countries such as Canada, Hong Kong, South Korea and Australia have dumped their trash in the Philippines. (Pittiglio, Reganati, & Toschi, 2017).

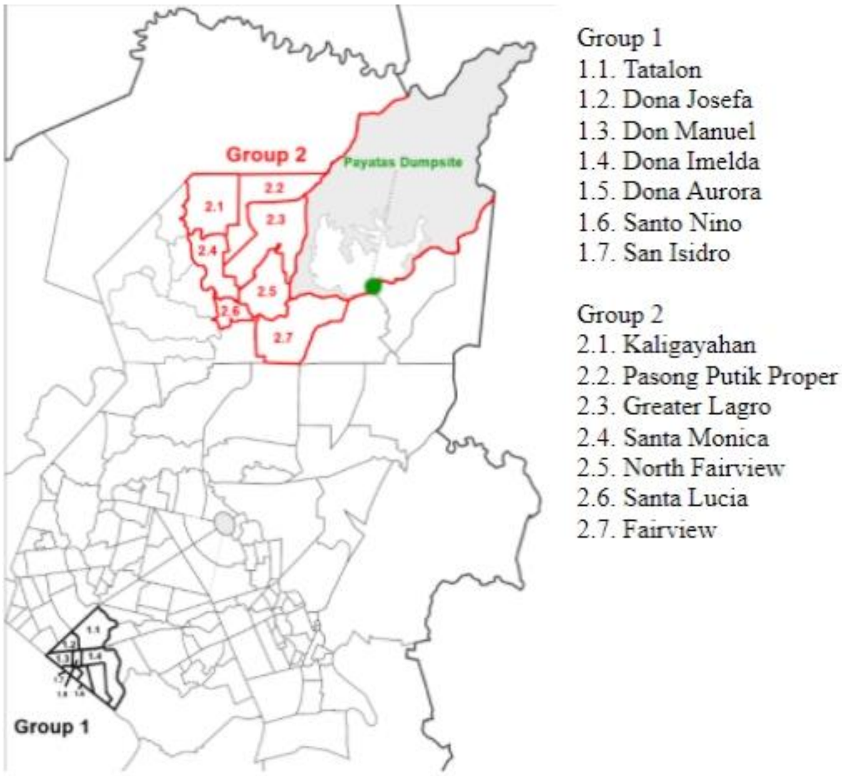


Figure 19: Maps of areas in Quezon City. Quezon City is included in a bounding box with lat-long coordinates ((14.60, 121.00);(14.78, 121.12))

For the above reasons and due to the lack of plastic waste management policy, we have chosen Quezon City as one of the target cities for this study, divided into two groups (see Figure 19), Group 1, which is located at the border of the city of Manila and Quezon City (4th district), and Group 2 located close to the Payatas dumpsite (5th district). The reason for choosing these 2 areas is because of the difference in population and policies of collecting waste.

4.2.1.1 Quezon City Group 1

The 4th district of Quezon city has 32 neighbourhoods but for the purpose of the study, only seven were chosen. The total population of these seven neighbourhoods is 92,283, Tatalon with the highest population. Note that the areas of all these seven places are less than a square kilometre, thus for the purpose of computing the population density, the area has been converted to hectares.

Table 8: Overview of the Demographic in Quezon City.

GROUP 1	Population (2015)	Area (km^2)	Population density (hectares)	Num. of street segments
Don Manuel	3,753	0.238	157.689	33
Doña Josefa	2,909	0.282	103.15	46
Doña Aurora	5,636	0.128	440	37
Doña Imelda	16,915	0.929	182.077	138
San Isidro	8,578	0.132	649	173
Santo Nino	10,278	0.193	532.5	299
Tatalon	63,129	0.925	682.4	152
Sources	City Population Website (n.d.-2), OpenStreetMap (Openstreetmap. (n.d.))			

Figure 20: Number of establishments in terms of percentage in Quezon City Group 1.

Figure 20 shows the distribution of venues in this first group of Quezon City. Restaurants have the highest percentage, followed by a group of other venues such as hospitals, shopping centres, cinemas, parks and coffee shops, whereas the third highest are private clinics.

4.2.1.2 Quezon City Group 2

Out of 14 neighbourhoods under the 5th district, for this study only seven of them were chosen. The neighbourhood of Kaligayahan has the greatest population, while Pasong Putik Proper has the biggest area. Moreover, Santa Lucia has the smallest population and also the least area (see Table 9).

Table 9: Overview of the Demographics in Quezon City group 2.

GROUP 2	Population (2015)	Area(km^2)	Population density	Num. of street segments
Fairview	53,151	3.12	17,035	430
North Fairview	41,154	2.01	20,474	200
Greater Lagro	22,764	4.24	5,368.86	427
Pasong Putik Proper	35,135	27.5	1,278.29	325
Kaligayahan	54,576	2.46	22,185	415
Santa Monica	46,553	1.65	28,214	309
Santa Lucia	25,577	0.642	39,839 (per hectare)	106
Sources	City Population Website (n.d.-2), OpenStreetMap (Openstreetmap. (n.d.))			

Figure 21 shows that the highest percentage distribution of venues is those grouped as "Others", which is the total of the venues less than 5% such as supermarkets, hospitals, train and bus stations, private clinics, and sports centres, among others. It is followed by restaurants, schools, and gas stations.

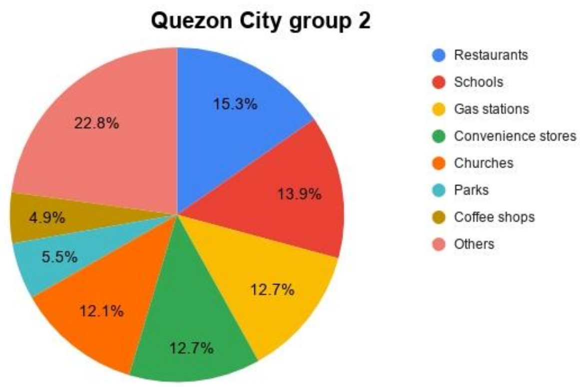


Figure 21: Number of establishments in terms of percentage in Quezon City Group 2

Lastly, Figure 22 shows the distribution of streets in the selected groups in Quezon City. The map further indicates that group 1, with a total of 878 streets, has fewer than group 2, which has a total of 2,212 streets. Furthermore, while in group 2 the neighbourhood with the highest number of roads is Fairview which is also the 3rd largest area, in group 1 the neighbourhood of Santo Nino has the greatest number of streets, even though it is one of the smallest in terms of area.

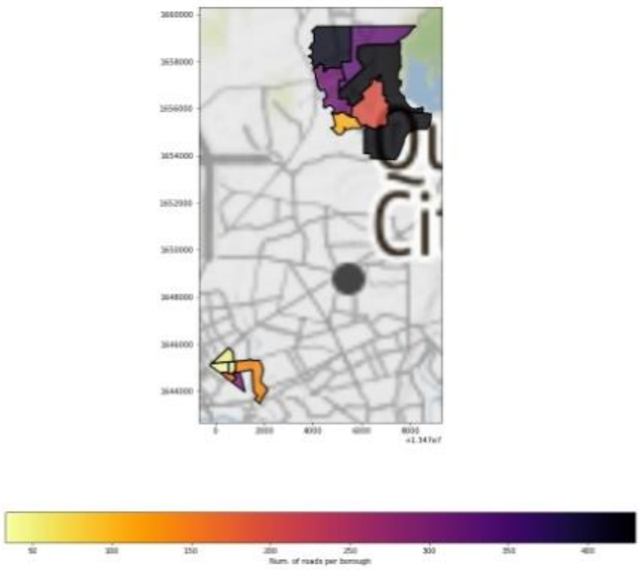


Figure 22: Distribution of the number of streets in the two groups in Quezon City, Philippines

4.2.2. India

Similar to the Philippines, we have divided the study of Indian cities into two groups: Group 1 located in the state of Punjab, where most of the cities still follow an open-air dumping policy, and group 2 located in the state of Gujarat, where they have already started with the trials of the waste management policy, and where they have the Pirana dumpsite, one of the main open dumping sites controlled by the state government. The map below shows India group 1 (see Figure 23(a)) and group 2 (Figure 23(b)). The cities in group 1 are Barnala (square 1.1), Dhaner (1.2) (both belonging to the district of Barnala) Moga (1.3) and Ludhiana (1.4), the latter two being city centre districts. Regarding group 2, Figure 23(b) shows the cities of Jamnagar (2.1), Ahmedabad (2.2), Gandhinagar (2.3) and Surat (2.4).

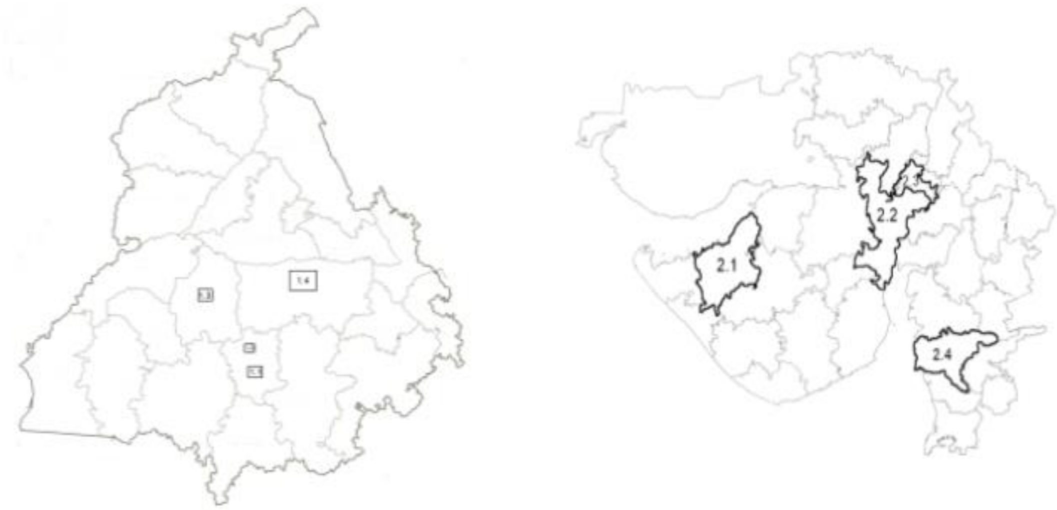


Figure 23: (a) Map of the cities in the state of Punjab; (b) Map of the cities in the state of Gujarat. Region (a) is included in the bounding box with lat-long coordinates ((29.63, 74.12); (32.34, 76,94)) and region (b) with lat-long coordinates ((20.63, 68.55); (24.61, 74.46)).

4.2.2.1 India Group 1

Table 10 shows the data for the four selected cities in the state of Punjab. The city with the largest population is Ludhiana followed by Moga. The biggest city in terms of area is Moga. However, Barnala has the highest population density. Also, there is insufficient data for the venues in Dhaner.

Table 10: Overview of Demographics in India group 1.

GROUP 1	Population	Area (km²)	Population Density	Num. of street segments
Barnala	190,619	11	17,329	134
Dhaner	2,140	10.09	212	4
Ludhiana	1,618,879	159	10,182	5,145
Moga	298,432	2,230	134	156
Sources	City Population Website (n.d.-3), OpenStreetMap (Openstreetmap. (n.d.))			

The distribution of venues in this group can be seen in Figure 24. The highest percentage of venues are hospitals followed by parks and by a group of other venues such as gas stations, restaurants, sports centres, cinemas, supermarkets, and private clinics, among others.

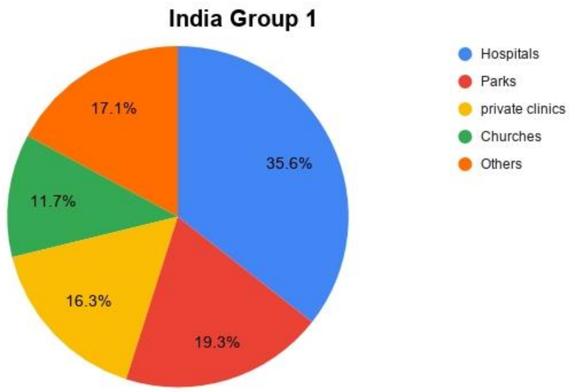


Figure 24: Number of establishments in terms of percentage in India Group 1

For this first group of Indian cities, it is worth mentioning that OSM does not comprise the administrative boundaries of these cities. For that reason, we needed to manually define the geographical boundaries of each of these cities by means of a rectangular bounding box as Figure 23(a) indicates. Then, we extracted the number of street segments included in each of these rectangular bounding boxes as shown in Table 9.

4.2.2.2 India Group 2

Group 2 is in the state of Gujarat, India. Out of 18 cities in this state, we have chosen the capital of the state, Gandhinagar, and three of the biggest cities in the state, Ahmedabad, Surat, and Jamnagar. Table 11 shows that the city with the greatest population and area is Ahmedabad, while Surat is the densest city.

Table 11: Overview of the Demographics in India, group 2.

INDIA GROUP 2	Population	Area (km^2)	Population density	Num. of street segments
Gandhinagar	1,391,753	2,140	650	3,760
Ahmedabad	7,045,313	6,968	1,011	17,275
Surat	6,081,322	4,549	1,336	4,472
Jamnagar	1,047,635	6,607	159	1,060
Sources	City Population Website (n.d.-4), OpenStreetMap (Openstreetmap. (n.d.))			

Figure 25 shows the distribution of venues in the second Indian group. Hospitals have the highest percentage of venues (more than 50%), followed by parks and other venues such as restaurants, gas stations, schools, supermarkets and coffee shops, being similar to the first group in the rank of venues.

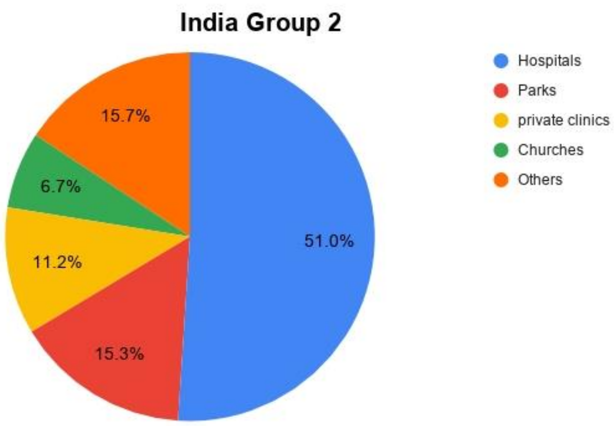


Figure 25: Number of establishments in terms of percentage in India Group 2

4.2.3. Selection criteria for the target cities

The target areas for this study lack a plastic waste management policy. They have been selected according to different values of size areas, population density and venue distribution. Whilst the areas in Group 1 of both countries represent small areas with different levels of population density, the areas in Group 2 allow us to study bigger areas for a range of population density values. Moreover, the venue distribution is also different among the target areas of both countries, being hospitals and parks the most relevant for Indian areas whereas restaurants and supermarkets are identified as the most frequent for Quezon city. It is worth noting that these two different distributions of top venues are similar to the venue distribution of the reference cities since the Indian areas seem more family friendly as in the Stavanger city whereas the Quezon City areas are more alike to the activity in New York, Madrid, and Malaga.

4.3. STATISTICAL ANALYSIS

Certain methodological and statistical models have been used to develop the final mechanisms in order to infer the number of bins in the above-mentioned target cities (Figure 9). This chapter discusses said methods and explains how it is essential to the study.

Regression analysis focuses on modelling techniques for the relationship between one or more independent variables and a dependent variable. Dependent variables are response variables that are a function of the independent variable while independent variables are predictors. In linear regression, parameters are often set and estimated to give the model the best fit and the dependent variable is used to set regression parameters and a random error. Simple linear regression analysis can be written in the following form:

$$y = \beta_0 + \beta_1 x + \varepsilon \tag{c}$$

where: y - dependent variable, x - independent variable,
β_0 - y intercept, ε - random error,
β_1 - the slope of the regression line

The dependent variable in this study is the number of bins in the target city's neighbourhood while the independent variables are some of the urban features of the target cities further discussed in Chapter 5.

In this study, weighted least squares (WLS) was used to calculate the actual values of the intercept and slope parameters of the linear regression formula. In order to understand this principle, a discussion of least square estimation is necessary. Least squares estimation finds the estimates of $b_0$and b_1 so that the sum of the independent variable and predicted response reaches the regression coefficients. The aim of this method is to determine parameter estimates by looking at the line closest to data points of the regression. Mathematically, the least square formula (d) and the least square estimates (e) can be written as:

$$(b_0, b_1) = arg \min_{(\beta_0,\beta_1)} \sum_{i=1}^{n} [\, y_1 - (\beta_0 + \beta_1 x_i)] ^2 \tag{d}$$

$$\frac{\partial}{\partial \beta_0} \sum_{i=1}^{n} [\, y_1 - (\beta_0 + \beta_1 x_i)]^2 = 0 \tag{e1}$$

$$\frac{\partial}{\partial \beta_1} \sum_{i=1}^{n} [\, y_1 - (\beta_0 + \beta_1 x_i)]^2 = 0 \tag{e2}$$

Weights are necessary in order to make sure that the acquired or used data fits the model and it is used when there is a higher chance of uncertainty of values due to the fact that there is a larger number of experiments, or the distribution is wider but datasets are lesser. Ordinary least squares (OLS) focus on the constant variance of errors (homoscedasticity), while WLS is used when the OLS assumption of constant variance of the errors is broken (heteroscedasticity). The simplest description of the formula is

$$w_i = \frac{1}{\sigma_i^2} \tag{f}$$

where $\sigma$is the reciprocal of each variance transformed into weight. Additionally, we can now change equation (d) into a weighted least squares estimate equation as (Seber & Lee, 2012; Yan & Su, 2009):

$$\hat{\beta}_{WLS} = arg \min_{(\beta_0,\beta_1)} \sum_{i=1}^{n} \epsilon_i^{*2} \tag{g}$$

The principal component analysis (PCA) which finds linear combinations of independent variables in order to prove the variations of the variables, was also used in this study (Yan & Su, 2009). The collection of different urban features from the reference cities is not efficient to fit the linear regression model with all features. Thus, for the reduction of the dimensionality of these independent features, PCA was used. In the simplest explanation of PCA, it can be expressed as the reformulation of the maximum likelihood solution of a latent model. In theory, if we let a dataset be X= $[x_1 \ldots\ldots\ldots x_N]$, then the sample vector and sample covariance matrix, $\bar{x}$ and Σrespectively, can be written as:

$$\bar{x} = \frac{1}{N}\sum_{i=1}^{N} x_i \quad \text{(h)}$$

and $$\Sigma = \frac{1}{N}\sum_{i=1}^{N}(x_i - \overline{x)}(x_i - \bar{x})^T = \frac{1}{N}XX^T \quad \text{(i)}$$

Lastly, to extract the PCA linear combinations of the variables, we can write it as (Kurita, 2019):

$$y_{1i} = a_1^T(x_i - \bar{x}), (i = 1, \ldots\ldots N) \quad \text{(j)}$$

Further use in this study and results are explained in section 5.

V - RESULTS

V - RESULTS

This chapter includes a discussion on the most relevant results of the main two components of the framework proposed in this thesis for the intelligent management of plastic waste, namely the smart bin system and the module for the urban planning of waste containers. It includes the combination of the analysis and outputs of chapters 3 and 4.

5.1. ANALYSIS OF THE SMART BIN SYSTEM

The following subsections explain the process involved in the smart bin component of the study. It includes the discussion on data collection and curation and displaying the analysis of forecasting the generation of plastics in household settings.

5.1.1 Evaluation Setting

The performance of the proposed smart-collaborative plastic-waste management system (described in Sec. 3) has been simulated in the city of Quezon, Philippines. The Philippines as a country has not completely managed the plastic-waste problem yet. The country is plagued with drainage blockages due to plastics that usually occur during floods (Atienza, 2020), posing a serious hazard to the population. Quezon City is the largest and most populous city in the Philippines, producing 262 tons of plastic waste per day. With 3,085,227 people and an area of 161.126 km^2. Multiple waste management plans have been tried and tested until today with different results (Premakumara, et al., 2018), showing that there is still a need for ideas and projects to improve waste management.

With the aim of assisting the management of plastics through household smart bins for people with disabilities, senior citizens, and COVID-19 affected residents, we have focused on data mainly about these profiles in the neighbourhoods of Quezon City. In an Ecological Profile report made by the government office of Quezon City in 2015[8] 34.92% of the total population are people

[8]Ecological Profile: https://quezoncity.gov.ph/wp-content/uploads/2020/12/QC-Ecological-Profile-2015.pdf

with mental, speech, orthopaedic, visual, or hearing disabilities, among others. According to the report, senior citizens are also included in this vulnerable group. In 2015, the estimated total number of people over 60 years old was 162,158.

In this study, three neighbourhoods (known as *barangays*) of three different districts in Quezon are involved in a simulation scenario: Don Manuel under districts Galas, Commonwealth under the district with the same name and Mariana in New Manila (See Figure 26). These neighbourhoods represent 0.13%, 6.75%, and 0.38% of the total population, respectively[9].

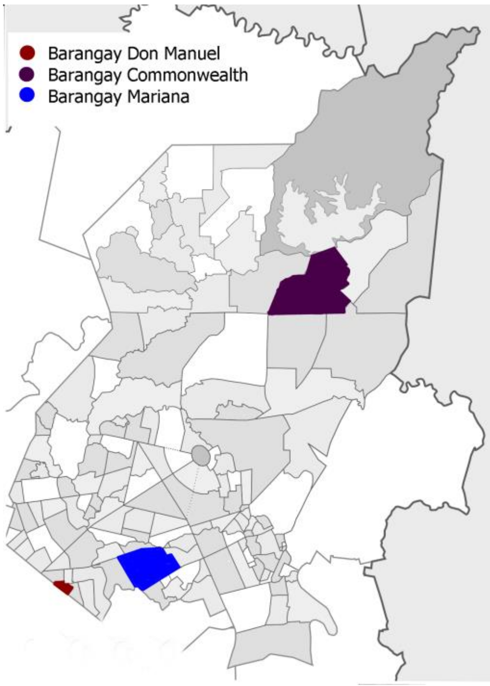


Figure 26: Location of the three neighbourhoods (Barangays) in Quezon City

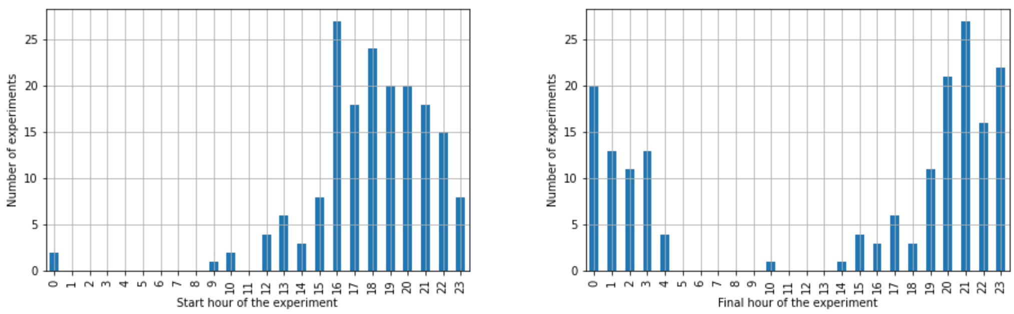
We have used this setting to allocate the different households simulated in the study and thus calculate the real distances for the route-planning algorithm described earlier in the paper. In terms of the socio-demographic profile of each neighbourhood, in Don Manuel, the computed age dependency ratio is 22 youth dependents to every 100 working-age population. Commonwealth's ratio is 43 and in Mariana, it is 17 to every 100 working-age population, respectively. Regarding

[9]Don Manuel, Quezon City: https://www.philatlas.com/luzon/ncr/quezon-city.htmlsectionBrgys

the old-age-dependency ratio in these 3 neighbourhoods, Mariana has the highest ratio of 11 to every 100. In terms of COVID-19, the city with the highest cases is Quezon City as of May 2021, with more than 150 active COVID-19 cases only in Barangay Commonwealth[10]

5.1.2. Data Collection

During the data collection stage, 176 different experiments, executed to collect data from the smart bin as described in section 3.2., were performed from 19 October 2019 to 30 January 2021. The average time length of each experiment was 235.18 min with a standard deviation of 65.48 min. Figure 27 shows the distribution of the start and end hours of the experiments. As observed, most of the experiments were taken during afternoons and evenings.



(a) Distribution of experiments based on the starting hour

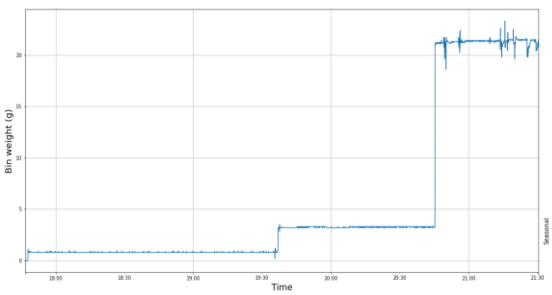
(b) Distribution of experiments based on the end hour

Figure 27: Distribution of the experiments based on their initial and end hour

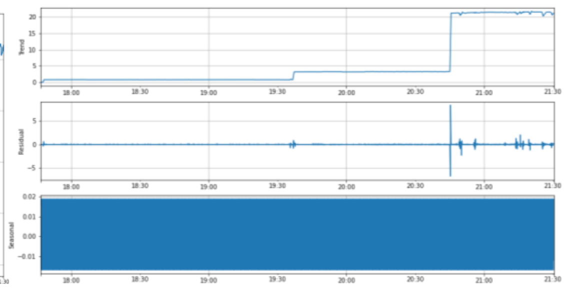
[10] Commonwealth, Quezon City: https://quezoncity.gov.ph/covid19counts/qc-covid-19-update-as-of-may-11-2021-8am/

5.1.3. Data Curation

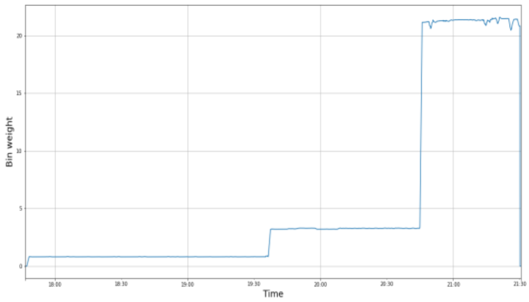
As an illustrative example of the data filtering process described in section 3.4., Figure 28(a) shows the time series of weights captured by the scale sensor during one of the experiments. As observed, the series is defined by a set of sharp weight increments. These moments indicate the time instant at which a user put one or more plastic items in the bin. Hence, the time series in Figure 28(a) reflects that the bin was used two times during the experiment since two sudden increments can be observed at different moments of the experiment. Apart from these increments, it is possible to observe some noisy points at the tail of the time series. This is because of the fluctuation given the high sensitivity of the weight sensor. The seasonal decomposition of the time series is depicted in Figure 28(b). As it can be seen, the time series is mainly defined by its *trend* dimension. This part of the time series indicates the clear evolution of the sensor values throughout the experiment, as it does not include the aforementioned noisy parts of raw values. Consequently, we were able to perform lightweight filtering of this time series by just keeping its trend component (Figure 28(c)). Please note that this trend does not suffer from the noise observed in the raw time series. Finally, the set of the 176 filtered time series was used for the next steps in the system, namely clustering and prediction.



(a) Raw time series of weights captured by the weight sensors in one of the experiments



(b) Seasonal decomposition of the time series following additive approaches



(c) Smooth version of the time series (trend component)

Figure 28: Data cleaning example

5.1.4. Generated Clusters

Regarding the clusters obtained from the filtered time series and based on the features described in Section 3.1.5, Figure 29 shows the silhouette score of the K-means algorithm for different values of clusters *k*. As observed, the *elbow* point of the plot occurs when *k* is set to three. This indicates that such several clusters provide the best fit regarding the similarity of the entities within each cluster and the dissimilarity among different clusters. The centroids defining each cluster based on the five input features as explained in Section 3.1.5 are shown in Table 12.

Table 12: Values of the descriptive features for the three clusters extracted from the experiments

Cluster	m	q_{25}	q_{75}	u	i
c_1	47.37	22.38	72.39	2.45	8.77
c_2	129.64	74.83	188.94	4.09	21.51
c_3	274.40	188.86	398.44	4.38	38.92

In our simulation scenario, these centroids are representing a particular user profile in terms of generating plastic waste when using the smart bin. As a result, each centroid could be mapped to a particular behaviour as follows:

- c_1: Family of two. One person with a disability who is working from home as an online teacher and another who works from home as a private money lender to small business owners. Both live in a one-bedroom flat in Barangay Don Manuel.
- c_2: Family of four. COVID-19 lockdown affected residents. One person is an essential worker, works as a jeepney/public transport driver, one person runs a small bakery business from home. Two kids who are studying from home. All living in a two-bedroom house in Barangay Commonwealth.
- c_3: Family of four with a caretaker. Husband and wife are working as doctors and nurses. Two kids who are in high school, and grandparents who stay at home. A caretaker comes to order/cook for the senior citizens. All living in a three-bedroom house in Barangay Mariana.

The rationale behind the assignment of these behaviours to each cluster is based on the actual information about these Barangays: Cluster c_1 in Don Manuel has one of the smallest areas in Quezon City with 0.238 km^2. Additionally, the highest age group percentage is 12.50% for 20 to 24 years old, and the generation of plastic waste is significantly low[11]. Cluster c_2 in Commonwealth has an area of 3.570 km^2. Additionally, the age group of 15 to 64 years old have the highest distribution by percentage at 67.74% and the average daily plastic-waste production amounts to 330 cubic meters per day[12][13]. Finally, the cluster c_3 in Mariana has an area of 1.664 km^2. The age group with the highest percentage is 25 to 29 with 10.86 and the average daily plastic waste amounts to 1.65 cubic meters per day[14](Asian Development Bank, 2016).

[11] Don Manuel, Quezon City: https://www.philatlas.com/luzon/ncr/quezon-city.htmlsectionBrgys

[12] Philippine Atlas: https://www.philatlas.com/luzon/ncr/quezon-city/commonwealth.html

[13] Barangay Population Statistics: citypopulation.de/en/philippines/quezoncity/

[14] Quezon City Statistics: Quezon City (Philippines): Barangays - Population Statistics, Charts and Map

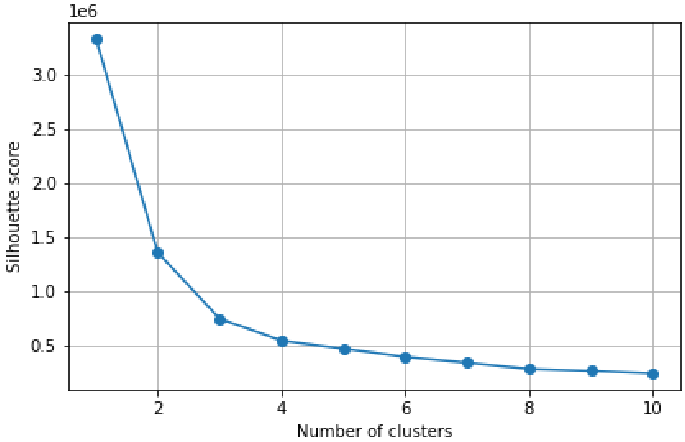


Figure 29: Silhouette score for different number of clusters *(k)*

5.1.5. Prediction Results

Given the predictor model in Section 3.1.7 aimed at forecasting the time when a bin is likely to be completely filled, we set Δ_m it to 5 g and $\Delta_t$to 200 s. This configuration was calculated by means of a grid search in the input space of both parameters. For this configuration, the solution had an average residual error of 2167 s (~36 min) $\pm$1390 s (~23 min). Figure 30 shows the residual error ($|t_{max} - \hat{t}_{max}|$) of this model for different time horizons. For instance, for a time horizon below 2000 s (~33 min), the error of the model was 1320 s (~22 min) on average. It is observed that the accuracy of the model degrades as long as the prediction horizon increases.

However, a meaningful drop in the residual error occurs for very long-time horizons between 12,000 and 14,000 s. The predictions for such horizons are provided by models fitted with W sets comprising the very first meaningful variations of an experiment (that is, the very first plastic items placed inside the bin). This might suggest that the initial set of plastic items inserted in a bin might actually define the whole waste behaviour of the target users to a high degree. Figure 31 shows the distribution of the residual error for each of the user profiles defined in Section 5.1.4. It is observed that the accuracy of the predictor was lower for the experiments with cluster c_3, with a residual error of 3352 s (~55 min.) on average. For the other two clusters, the error was around 2000 s (~33 min.).

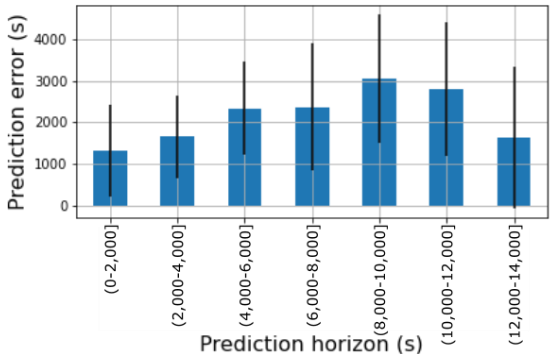


Figure 30: Residual error of the prediction model for different time horizons.

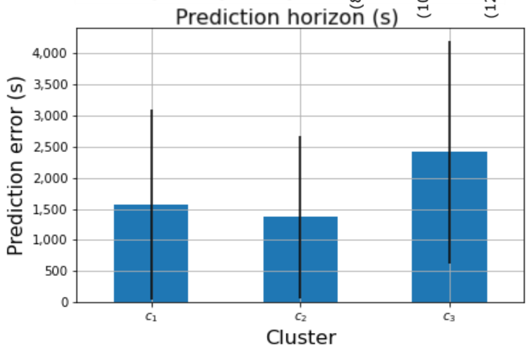


Figure 31: Residual error of the prediction mechanism given the identified clusters

From Figures 30 and 31, it is observed that the predictor error ranges between 1200 and 4600 s (20 and 76 min). These predictions are used by the route generation algorithm to compute the pick-up hour for each bin as stated in Section 3.8. We believe that this error range is small enough to generate a pick-up hour close enough to the actual moment when the bin is full. In the worst case, users will have their bin completely full for around 76 min before a waste-picker arrives at their home. This seems a sensible time period to wait given the benefit that the system would bring to the user.

Finally, the web application included in our proposal (Section 3.6) displays the time series of each experiment along with its associated prediction as shown in Figure 32. This allows the timely control and validation of the state of each bin in a real-world deployment.

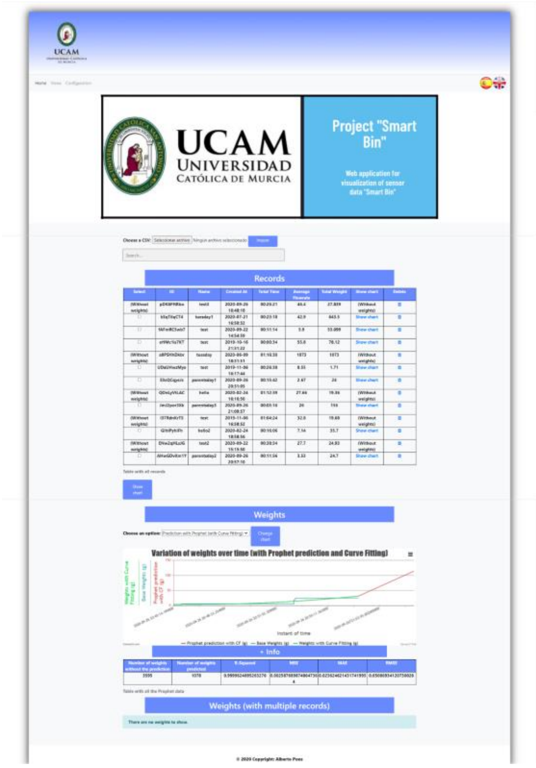
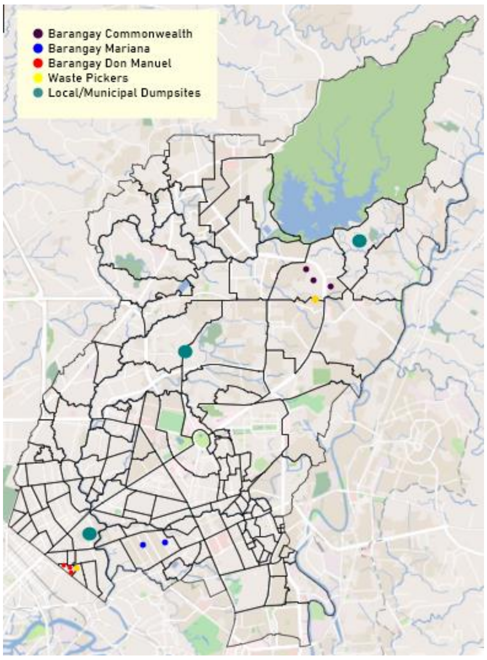


Figure 32: Main view of the web application. The upper section displays the list of experiments whereas the bottom one shows the time series of one of them

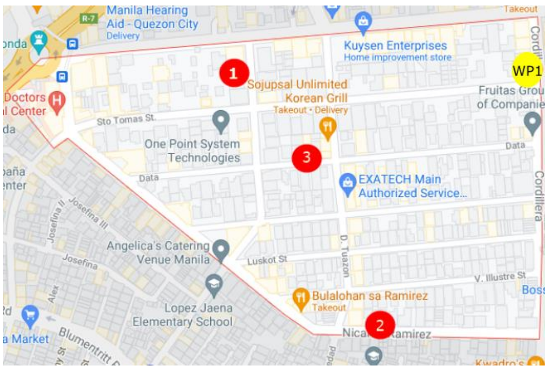
5.1.6. Composition of the Collection Routes

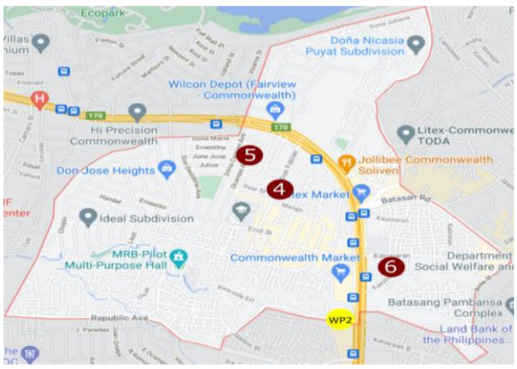
The evaluation of the route generation algorithm is explained in Section 3.1.8 has been performed in a simulated test-bed scenario within Quezon City for the clusters defined in Section 5.1.4.

To run the simulation, eight household smart bins and two waste-picker locations were defined within the city area. Then, each bin location was linked to a particular cluster for plastic-waste behaviour. As shown in Figure 33, six smart bin locations in the south of the city were assigned to clusters c_1 (locations l_1, l_2, l_3) and $c_2(l_4, l_5, l_6)$, respectively, and two more in the north to c_3 (l_7, l_8). The set of waste-pickers was defined as $WP= \preccurlyeq wp_1, wp_2 \succ$. Furthermore, we also considered the location of three municipal dumpsites at Quezon City. They are depicted as green dots in Figure 33(a). Please note that these dumpsites are an important contextual factor to be considered. This is because waste-pickers need to deposit the plastic waste from the target houses in any of these dumpsites during their collection routes.



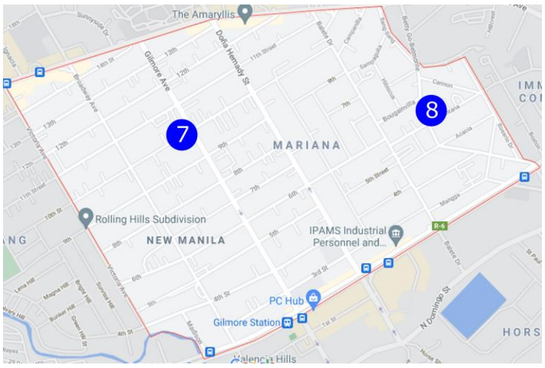
(a) Overview of the city. The black solid lines indicate the boundaries of the neighbourhoods.





(b) Location of the smart bins for cluster $c_1$and for waste-picker wp_1

(c) Location of the smart bins for cluster $c_2$and for waste-picker wp_2



(d) Location of the smart bins for cluster c_3

Figure 33: Quezon City showing the location of the houses with smart bins and waste pickers homes. Each coloured dot indicates a particular location. The red dots belong to the cluster c_1, the dark red ones belong to the cluster $c_2$and the blue ones belong to c_3.The waste-picker houses are shown as yellow dots and the dumpsites are depicted as green dots.

Once the scenario was set, each smart bin location l_i was associated with a subset ε_i of the data collection experiments (out of 176) by considering its cluster (Section 5.2.2.). For example, ε_7 comprised experiments related to the cluster c_3. In this manner, we simulate a real-time behaviour of the use of the household smart bins by means of an iterative approach. For each day in the study period (from 19 October 2019 to 30 January 2021 according to Section 5.1.2., we extracted a particular experiment related to that day, if any, from each setε_i. Next, for each experiment, we kept the weight evolution of its first k items. A particular experiment gave rise to as many *sub-experiments* as its total number of items (see Table 13). Then, a prediction for the target *sub-experiment* of each location was generated giving rise to a set or pick-up points $P = \preccurlyeq (l_1, \hat{t}_{max,1}), .., (l_n, \hat{t}_{max,n}) \succ$ (n ≤ 8). Moreover, the two waste-pickers had the following range of available hours, H_{wp1} = (16:00, 23:00), H_{wp2} = (20:00, 02:00). Consequently, the simulated real-time behaviour can be regarded as a two-level loop, one moving across the days and a nested one moving across the number of items of the experiments.

Table 13: Number of sub-experiments for each location used across the simulation

Location	Num. of Sub-Experiments
l_1	369
l_2	233
l_3	151
l_4	379
l_5	217
l_6	109
l_7	223
l_8	124

The set of pick-up points along with the range hours of the waste-pickers fed the ILOG solver to compose the required collecting routes. To do so, we made use of the implementation provided by the *OR-tools* suite[15], open-source software for optimization. This suite requires the time distances among the target locations to compose the final routes. To study the impact of the means of transport used by the waste-pickers to cover the routes, we defined distance matrices based on three means of transport, namely bike, car and on foot. The travel times were calculated by means of the *Google Maps* web service[16]. For completeness, Appendix A shows the travel time matrices for each means of transport (see Table A1 for bike, Table A2 for on foot and Table A3 for car). Furthermore, we also considered that the number of plastic-waste bags that a waste-picker can carry at the same time depends on the specific means of transport. It was assumed that a waste-picker can carry only two bags at the same time when moving on foot or by bike and eight when moving by car. This was done by forcing the route composer to include a visit to the closest dumpsite when several bags are reached.

[15] OR-tools suite https://developers.google.com/optimization

[16] Google Maps: https://www.google.com/maps

For each route, its *collection rate* was calculated. This metric indicates the percentage of bins included in the route that would have been eventually collected by the waste picker before they were filled. This is possible to calculate because each route comprises the collection hour for each bin and the actual filling hour of the bin, which is available through the original experiment. Figure 33 shows the collection rate for the three means of transport. This rate is shown taking into account the number of items that were already inserted in the bin when the route composition algorithm was performed. For example, the leftmost blue column shows that the average collection rate for routes based on predictions generated when there were two plastic items in the bin and the waste-pickers moved on foot was 0.18 (i.e., 18% of the bins were collected before they were filled).

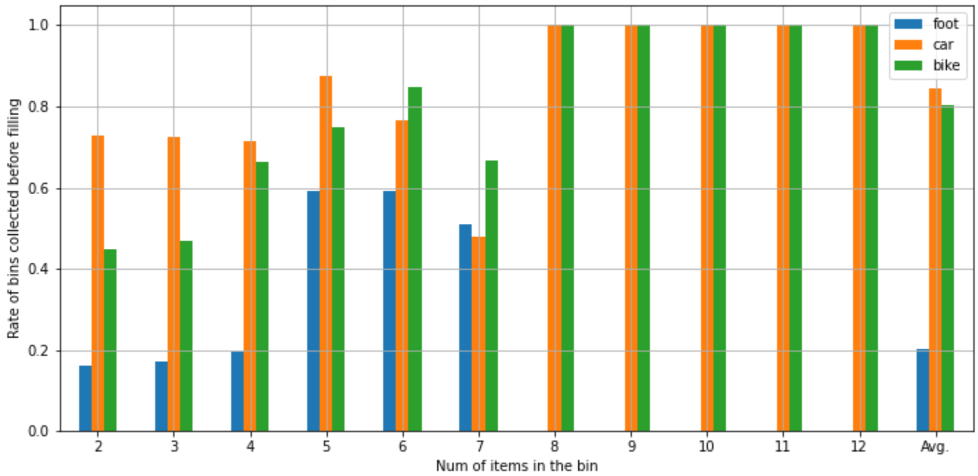


Figure 34: Collection rate per means of transport and number of items in the bin

According to Figure 34, the solution achieved a collection rate of around 0.8 on average when bikes or cars were used as means of transport. However, this rate remarkably dropped when waste-pickers moved on foot (see the last *Avg.* column in Figure 34). This is because this means of transport required very long walks to the dumpsites, requiring extra time with respect to the other means of transport. Another interesting finding is that the collection rate when using bikes and cars increases as long as the predictions are based on a larger number of items. As a matter of fact, their rate equals 1 (i.e., all the bins are collected before they are actually filled) when the predictions used by the ILOG solver rely on 8 or more items regardless of the means of transport. The reason for this behaviour is that the predictions based on a low number of items have a larger variability than those based on a high number. This high variability makes the route composer receive input pick-up points with very different filling hours, and therefore it is not able to find a suitable route covering all the locations in most situations. However, if the estimated filing hours rely on predictions based on a larger number of items, they tend to be more homogeneous covering a smaller range of hours within a day. This makes it easier for the solver to find a feasible pick-up sequence. Regarding the predictions based on a lower number of items, the rate is usually higher when the waste-pickers use cars or bikes.

Regarding the results when waste-pickers move on foot, it is observed a different behaviour than for the other two means of transport. Although the system achieved collection rates from 0.18 to 0.59 when predictions were based on seven or fewer items (see Figure 34), it was not able to compose collection routes when a larger number of items were included in the prediction step. This is strongly related to the homogeneity of the predictions explained in the previous paragraph. Since the range of hours is smaller in this case, the route composer is not able to find a route that covers all the houses along with the required visits to the dumpsites. Furthermore, Figure 35 shows the collection rate for each of the days under study. As observed, the rate fluctuations for the routes covered on foot and by bike were higher than for the routes covered by a car. Those walking and biking routes had a rate of 0 in several days indicating that it was not possible to compose a route able to visit any of the bins' houses before the filling hour. However, the car-based routes exhibited higher stability with rates above 0.7 on most of the days.

As an illustrative example of a specific route, given the following pick-up points $P = \preccurlyeq (l_1, 20), (l_2, 20), (l_3, 19), (l_4, 23), (l_5, 22), (l_6, 21), (l_7, 18) \succ$, the route solver is able to compose the following route for wp_1 when she moves by bike,

$$S_{wp1} = \preccurlyeq (l_7, 18) \rightarrow (l_3, 19) \rightarrow (DS_2, 19) \rightarrow (l_1, 20) \rightarrow (l_2, 20) \rightarrow$$
$$\rightarrow (DS_2, 20) \rightarrow (l_6, 21) \rightarrow (l_5, 22) \rightarrow (DS_3, 23) \rightarrow (l_4, 23) \succ$$

As a result, the waste-picker would be able to reach bins at l_1 and l_2 and leave their bags at dumpsite DS_2 during the same hour range, since it only takes 4 min to go from l_1 to $l_2$and 15 min to go from l_2 to DS_2 according to the time matrix for bike routes Table A1. The same occurs for l_4 and DS_3 because it takes 49 min to moves from one location to the other.

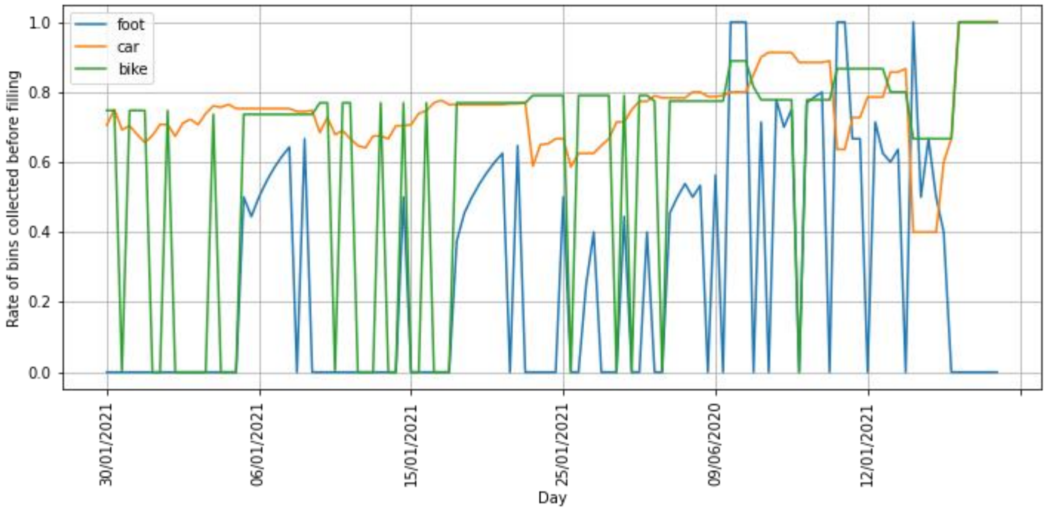


Figure 35: Collection rate per means of transport and day.

5.2. RESULTS OF THE URBAN PLANNING ANALYSIS FOR PLACING WASTE CONTAINERS

In this section, we used the reference city data (chapter 4.1.) to infer the number of bins in the target cities (chapter 4.2). To this end, we performed a statistical analysis in which the number of bins was identified as the output variable whereas the rest of the variables described in the previous sections (population, area, population density, number of street segments, average distance of bins and types of venues) were identified as the independent variables. The IBM SPSS statistics software (version 27.0) was used to perform the statistical analysis described below on the data collected from the reference cites comprising a total of 32 instances, namely the boroughs/districts of the 4 reference cities. Then, the resulting model was applied to the target cities to estimate the number of bins in these cities, as shown at the end of the section.

The steps followed in the statistical analysis are described next. In the first place, a linear regression analysis was performed on the reference city data to identify the most relevant variables to estimate the number of bins, excluding the variable “types of venues” due to its large range of values (it was included in the next step). Through this analysis, we obtained the linear regression models including the most relevant variables along with the coefficient of determination (R^2) which measures the confidence in the obtained models. This coefficient ranges from 0 to 1, the higher the R^2 value, the better the model predicts new values. By applying the SPSS automatic linear modelling stating as a goal the improvement of the model accuracy, the results yielded a linear regression model with anR^2 of 0.45, identifying the population density and the number of street segments (NSS) as the most significant variables, with an influence in the calculation of the number of bins of 41% and 17%, respectively (see Figure 36). It is worth mentioning that the importance of the population and area size for calculating the number of bins is captured thanks to the population density variable.

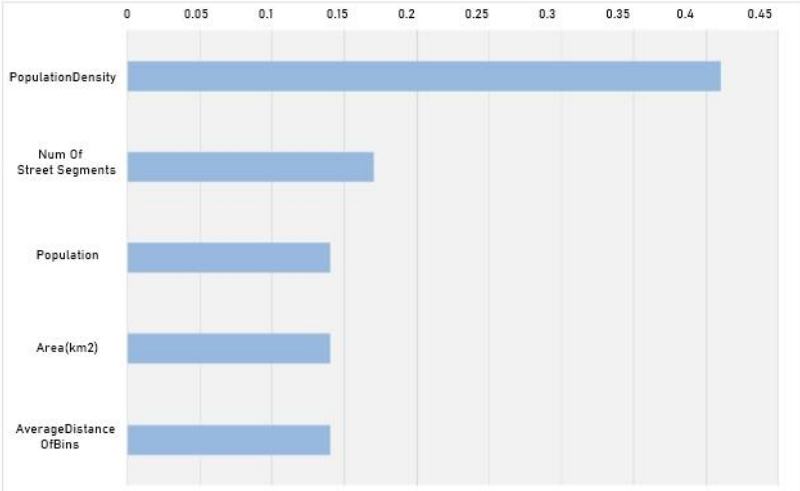


Figure 36: Relevance of the input variables in the linear regression model for estimating the number of bins.

Next, we focused on enriching the model with the venue data extracted from the reference cities. Since the number of venue types was rather high (27 different categories were extracted from OSM), they could not be integrated directly into the regression model as input variables as it would enlarge too much the input dimension of the model. As a result, we performed a feature selection process to filter the most relevant types of venues for bin allocation. To do so, the Principal Component Analysis (PCA) algorithm was applied (Wol, Esbensen, Geladi. 1987). In brief, this algorithm is able to detect the axis comprising the largest amount of variance in a dataset. PCA can be used for feature selection on the basis of the variable coefficients on the uncovered axis. Hence, we firstly represented these venues following a binary representation. This way, we composed a new matrix V with rows representing the reference neighbourhoods and 27 columns (each one representing a type of venue). A feature took 1 or 0 as a value depending on whether the latent type of venue is present in the neighbourhood or not. Then, a PCA instance was fed with this matrix. After that, we just kept the top 4 features with the highest coefficients in the first PCA axis. These features correspond to the following pairs of types of activity/venue:

- amenity/restaurants (coeff. 0.2479)
- leisure/parks (coeff. 0.2442)
- buildings/schools (coeff. 0.2439)
- shop/supermarkets (coeff. 0.2438)

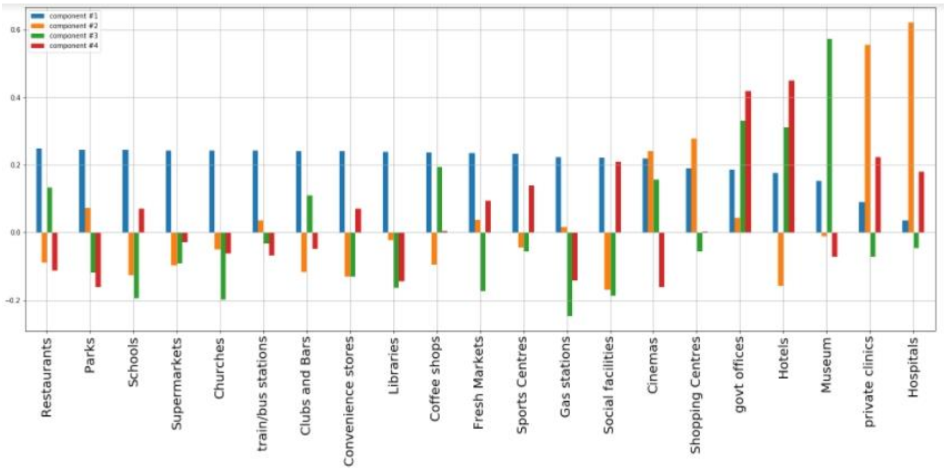


Figure 37: Venues' weights given the first four components of PCA.

For the sake of completeness, Fig. 37 shows the weights of each venue given the first four components extracted by the PCA. In that sense, the venues in the x-axis are sorted by their weight in the first component in descending order. This set of relevant venues can be regarded as dimensions of the latent predominant land use of a region from the point of view of bin allocation. Finally, the matrix V'⊂V comprising the columns of these four features was integrated in the initial dataset as new independent variables to feed and evaluate the models. This way, we were able to enrich the analysis with a simplified view of the distribution of venues in each of the regions.

Table 14: Model Summary of WLS

Multiple R	0.849
R square	0.721
Adjusted R square	0.667
Standard Error	0.164

Finally, applying the Weighted Least Square (WLS) analysis to the variables obtained in the two previous steps (i.e., population density, NSS and the four predominant land use categories represented as binary values 0/1), it was obtained an R-squared value of 0.721 (see Table 12) using NSS as the weight variable. In a nutshell, for small data sets, it is more efficient to use WLS to add weight to precise measurements. It is also used for data sets intended for prediction, estimation, and calibration (Sulaimon, 2015). The coefficients for the rest of the variables were weighted with the NSS by the following formula:

$$Weight = \frac{1}{Number of Street Segments(NSS)^2} \quad \text{(k)}$$

Table 15: Coefficients and standard error obtained from the Weighted Least Squares analysis

	B	**Standard Error**
Number of bins	1456.921	301.459
PopulationDensity	-0.01	0.013
ShopSupermarkets	-1344.143	428.79
LeisureParks	-537.667	373.329
AmenityRestaurants	-1429	300.669
BuildingSchool	-1306.106	284.667

As a result, it was obtained the following formula (see Table 13 for variables' coefficients) to estimate the number of bins of an area:

$$NumberofBin = 1456.921 - (0.010X_0) - (1429X_1) - (537.667X_2) - (1306.106X_3) - (1344.143X_4) \quad (1)$$

where:

$X_0 - PopulationDensity$
$X_1 - AmenityRestaurants$
$X_2 - LeisureParks$
$X_3 - BuildingSchools$
$X_4 - ShopSupermarkets$

Table 16 shows the numbers of bins estimated for the target areas after applying this result (the predominant land use for each target area indicates which of the four dimensions identified by PCA algorithm takes value 1 in the area). As can be seen, for areas in Quezon City Group 1 and India Group 2, the number of bins corresponds with their population density and number of street segments as for similar reference cities. However, some values are unexpectedly high for some specific areas, as for example in Dhaner, with an area of 10 square kilometres but with a small population of 2,140, has a number of bins of 1,454. These improbable values could be due to the lack of information about the predominant land use in (k) when it is different from restaurants, schools, supermarkets, and parks in those areas, or due to an imbalance of data in terms of population or area.

Table 16: Weighted Least Squares equation results for target cities

Group 1 Quezon City, Philippines	Predominant Land Use	Proposed Number of bins
Don Manuel	amenity/restaurants	26.34
Doña Josefa	amenity/restaurants	26.88
Doña Aurora	building/schools	146.41
Doña Imelda	amenity/restaurants	26.10

San Isidro	building/schools	114.32
Santo Nino	amenity/restaurants	22.59
Tatalon	building/schools	143.99
Group 2 Quezon City, Philippines		
Fairview	leisure/parks	748.90
North Fairview	amenity/fuel	1252.18
Greater Lagro	leisure/parks	865.56
Pasong Putik Proper	amenity/restaurants	15.13
Kaligayahan	amenity/place of worship	1235.07
Santa Monica	amenity/place of worship	1174.78
Santa Lucia	shop/convenience	1058.53
Group 1 Punjab, India		
Barnala	amenity/hospital	1283.63
Dhaner	-	1454.80
Ludhiana	leisure/parks	817.43
Moga	amenity/place of worship	1455.58
Group 2 Gujarat, India		
Gandhinagar	leisure/parks	912.75
Ahmedabad	amenity/hospital	1446.81

Surat	amenity/hospital	1443.56
Jamnagar	amenity/hospital	1455.33

VI -INTEGRATION OF THE HOUSEHOLD SMART BIN AND URBAN PLASTIC WASTE PLANNING APPROACH: A CASE STUDY FOR QUEZON CITY, PHILIPPINES

VI - INTEGRATION OF THE HOUSEHOLD SMART BIN SYSTEM AND URBAN PLASTIC WASTE PLANNING APPROACH: A CASE STUDY FOR QUEZON CITY, PHILIPPINES

This chapter shows a proof of concept on the functioning of the holistic plastic waste management framework proposed in this thesis. To this end, we focused on the neighbourhood of Don Manuel, Quezon City, Philippines as the scenario where both the household smart bins are used and the urban planning for the waste containers is taken into consideration for creating routes for waste pickers. The number of bins used in this chapter is computed from the urban planning module and the composition of routes are from the household smart bin module.

As described in Chapter 5, Quezon city is considered the most populous city in the Philippines, which also had the most number of COVID-19 cases and with 34.92% of the population with disabilities and senior citizens. Additionally, based on the results of the Weighted Least Squares model to determine the total number of bins in the city (section 5.2), the number of municipal bins needed in Don Manuel is 26.

6.1 SETTING DESCRIPTION

The present study focuses on the neighbourhood of Don Manuel, Quezon City, Philippines, as the common neighbourhood presented in the household smart bin framework (section 5.1.1 and 5.1.6) and urban plastic waste planning approach (5.2). The evaluation of the smart bin framework included 3 household smart bins and 1 waste-picker. Table 15 shows the exact location of these household smart bins and the waste picker in the neighbourhood. In order to be consistent with chapter 3, the neighbourhood of Don Manuel and these locations are listed in cluster 1 of the user profiles explained in section 5.1.4.

Table 17: Locations of the smart bins and waste-picker in Don Manuel, Quezon City (See Figure 33(b)).

Don Manuel	Address
Smart bin 1	21 Matimyas Street
Smart bin 2	89 Nicanor Ramirez Street
Smart bin 3	27 Data Street
Waste-picker 1	51 Cordillera Street

Figure 38 shows the proposed locations of these 26 municipal bins including the household bins around Don Manuel. Since the urban planning module does not specify the location of the 26 bins, we manually set the location of each bin. In that sense, all bins are equally distributed in the geographical map of Don Manuel. The locations of these bins are within the range of 100-250 meters from each other, which is estimated by computing the minimum distance of bins by dividing the area in hectares (23.8 hectares) with the proposed number of bins (26). These bins are going to be used by the waste pickers to throw the plastic bags collected from the household bins.

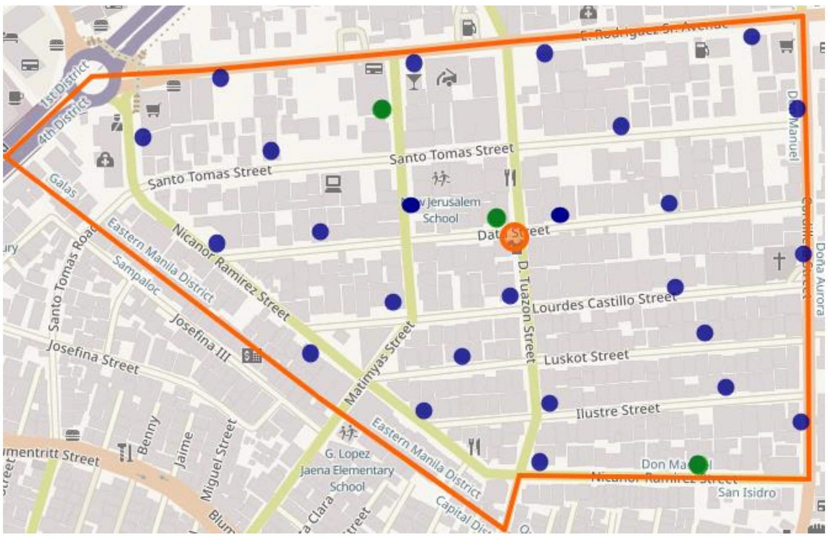


Figure 38: Visual representation of the municipal waste bin (in blue dots) and household smart bin (in green dots) locations.

6.2. RESULTS

Given the aforementioned configuration of on-street containers, we evaluated the performance of the smart bin framework as presented in chapter 5.1.6. The collection rate which indicates the percentage of bins including the route composition for the waste pickers is presented in this subchapter.

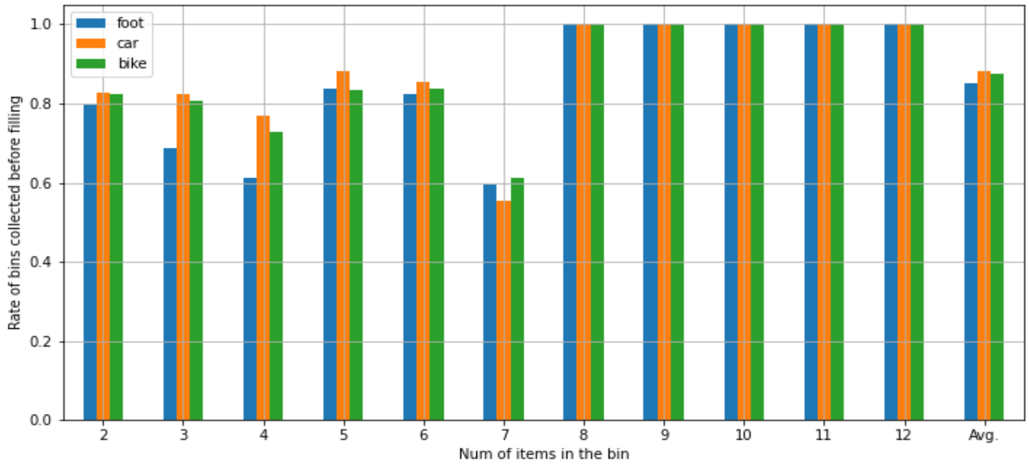


Figure 39: Collection rate per means of transport and number of items in the bin

Figure 39 shows that the solution achieved an average collection rate of over 80% for bikes, cars and on foot as a means of transport. The rate of collection for bikes and on foot collection is greater than 60%, which in conclusion suggests that the proposed system with the use of waste pickers and municipal plastic bins will be a sustainable system that supports the use of bicycles and going from one place to another on foot rather than by car. An additional interesting finding is that when the predictions are based on more items, the collection rate also increases. This is contrary to the findings included in chapter 5 (figure 34) which achieved a collection rate of 0.8 with bikes or cars as means of transport, while on foot the rate significantly drops. Additionally, in figure 34, the collection rate per means of transport for on foot transport never reached 0.6 and the average is at the rate of 0.2, while in figure 39, transport on foot and by bike are always at 0.6 and higher with an average of higher than 0.8 for both means.

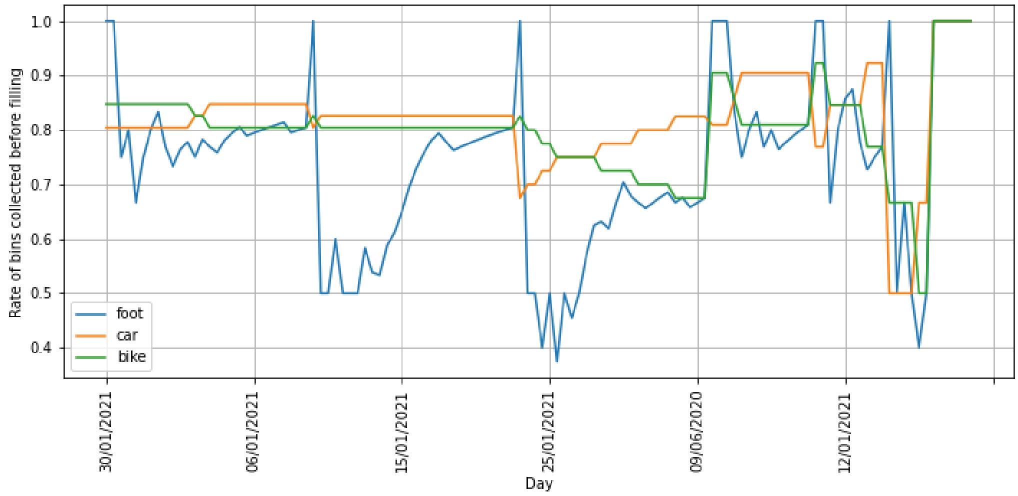


Figure 40: Collection rate per means of transport and day.

Furthermore, Figure 40 also shows the collection rate for each of the different days of the study. The rate fluctuations for the routes covered on foot is higher than the routes covered by car and by bike. In comparison to figure 35, car-based routes showed higher stability where they had rates above 70% most of the days and foot-based routes had a rate of 0 on normal days, while in figure 40, walking and biking routes never reached the rate of zero.

6.3. EVIDENCE OF THE IMPORTANCE OF WASTE PICKERS AND MUNICIPAL WASTE BINS IN DON MANUEL

This evaluation comprises the comparison among the existing dumpsite locations in the neighbourhood of Don Manuel and the 26 on-street containers computed through statistical analysis, both presented in Chapter 5. This differentiation also involves the waste pickers and household smart bins presented in chapter 3. The waste pickers from each cluster will be able to put collected plastic waste from the household to the municipal waste bins instead of the dumpsites closest to them. The most significant change seen while comparing figure 34 and 41 is the average rate of collection on foot, which is less than 20% and more than 80%, respectively.

The inclusion of dumpsites in the matrices and collection time series can make a huge difference in terms of the collection rate of the more sustainable means of transport such as by bike and on foot (Figure 41). Collection rates by car have increased since the dumpsite is farther from the household bins, waste pickers and the location of municipal bins. This proves that the concept of municipal plastic bins will gradually help the environment not only with the proper disposal of plastics but also with the environmental friendliness of the means of transport collection.

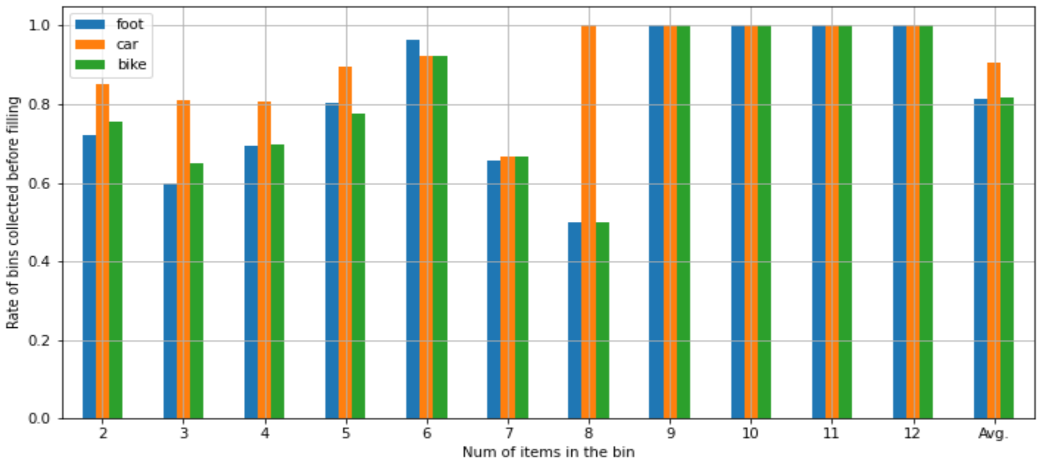


Figure 41: Collection rate of bins per means of transport with the inclusion of municipal bins and dumpsites.

Additionally, unlike figure 40, the rate of fluctuation for the transport of bikes and on foot is higher than figure 42 where the rate actually reaches zero during some days which indicates that it was not possible to compose a route able to visit any of the bins. With the dumpsites, the rate of fluctuations of the routes covered by a car is higher or more stable than the other two.

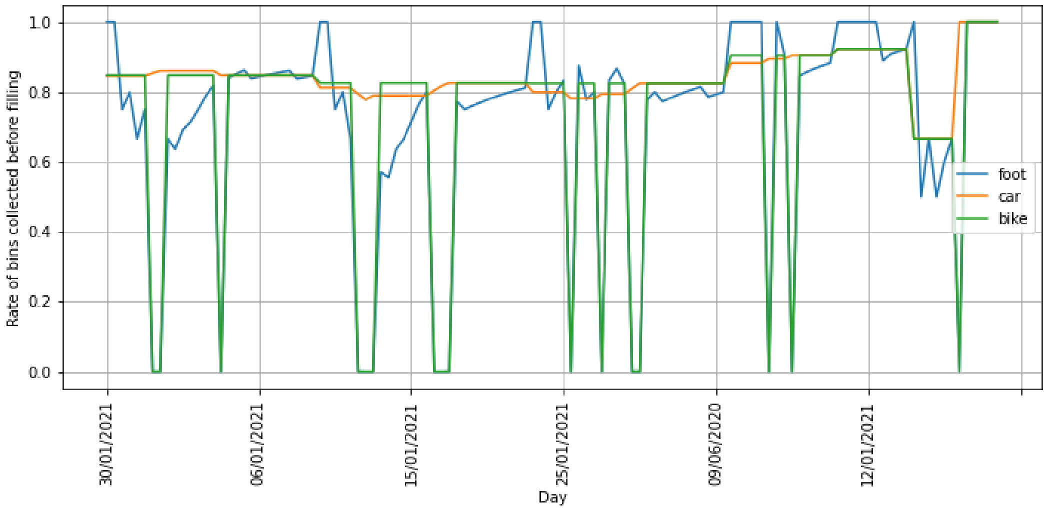


Figure 42: Collection rate per means of transport and day for route composition

All in all, with the integration of the household smart bin system which includes the route composition mechanism and the urban plastic waste planning approach, the combination of having waste pickers and municipal plastic waste bins in one neighbourhood is sustainable and efficient in terms of collecting plastic waste and management of plastic waste in a municipal level. The best and most efficient collection showed an average rate of 80% for bikes, on foot and cars as means of transport based on the number of items in the bins. In conclusion, the waste pickers' collection rate from household bins to the municipal bins implemented by the urban plastic waste planning module is more competent than having waste pickers' routes from household bins to dumpsites.

VII - CONCLUSIONS

VII. CONCLUSIONS

The control of plastic waste in urban settlements represents a major challenge in many Eastern countries. As stated elsewhere (Chung, 2012), the impact of visual pollution of plastic waste could eventually damage the residents' abilities to enjoy a view, which can further lead to a negative perception regarding comfort, psychologically and visually. Improper disposal of plastics resulting in microplastics is also harmful to the environment, wildlife ecosystem and also human health (Vethaak & Legler, 2021). Furthermore, plastic production has significantly increased during the COVID-19 pandemic. Disposable products such as masks, PPE kits, and gloves have doubled the plastic waste, which makes communities and countries in need of new and creative waste-management solutions including the installation of plastic bins in urban areas. Additionally, citizens with disabilities, seniors and those in COVID-19 quarantine may have difficulties throwing the plastic waste on a daily basis.

Overall, a collaborative solution for a household plastic waste collection focused on different groups was achieved through this thesis. This solution was composed of a lightweight smart bin used to collect and forecast the amount of plastic waste in each bin. The results from the predictor model were forwarded to an algorithm to generate optimum routes for waste-pickers or residential garbage collectors that allows them to maximize plastic waste collection efficiency within minimal time. Additionally, an urban planning method based on the use of open data to estimate the number of plastic bins in developing cities that are struggling with plastic waste management was also proposed. Thus, a set of variables and data related to the management of plastic bins in several Western cities available in their open-data web portals were collected, with the aim to infer the number of bins in the cities of two Eastern countries.

The specific objectives proposed in this thesis were achieved in the course of the work. Thus, the first specific objective *"planning locations of the municipal plastic waste containers through open data and statistical analysis for developing countries with zero to a limited number of plastic bins"*(chapter 4) in which demographics, number of venues, number of street segments and bin location from New York City, Malaga, Madrid, and Stavanger were used to execute a linear regression and weighted least square regression analysis to determine the total number of bins needed in two different groups of Quezon City, Philippines, and some cities in the states of Punjab and Gujarat, India. The venue distribution of each district was weighted with the number of street segments in order to obtain an R-squared value of over 0.7.

The second specific goal was *"to develop a smart bin based on a low-cost sensor set to monitor the fill level of the bin in household environments"* (chapter 3). A high-sensitive Acaia weight scale was used as a sensor placed under the bin to weigh the plastic waste bin put inside the bin. Since plastic wastes usually have low weight, an accurate sensor was important to detect what plastic item was in the container. Additionally, *predicting the weight of plastic bins and the number of plastic items in the bin through statistical analysis* (chapter 3.7) was also achieved as explained in section 3.2 with the use of a weight sensor.

The results from the predictor model are forwarded to a route-planning algorithm to generate optimum routes for waste-pickers or residential garbage collectors that allows them to maximize the number of bins collected in the shortest time. This solves the next specific objective which is *"composing a route for waste pickers through three different means of transport with the predicted weight of plastic bins and time of route from each registered waste picker from their point to the household and municipal bins"* (chapter 3.8). This has been validated through a simulation in Quezon City (the Philippines) by identifying three user profiles related to plastic-waste generation in eight different locations and with the collaboration of two waste-pickers using 3 different means of transport. The collection rate for this simulation resulted in an average of above 0.8, i.e., more than 80% of the household bins were collected before they were completely filled. The solution falls under the category of vehicle routing problems with time windows.

The final specific objective is to *"develop a framework that will store, analyze and display data acquired from the smart bin sensors for different purposes for instance, for the municipal authorities to analyze plastic waste trends in the region, for people with disabilities, senior citizens and Covid-19 affected residents to be able to call or request for waste pickers and for waste collection services and waste pickers to be able to know the location of the house where plastic waste needs to be collected and the location of the municipal bins where the plastic waste can be disposed of properly through optimal collection routes"*(chapter 3.6). This is achieved through a web application that has a continuous data visualization of the weighted data for plastic waste in the smart bins. It also displays the time series of each bin with the associated prediction of weight and composition of routes.

Finally, it is noteworthy that the results of this thesis could serve as a basis for the development of applications and the renovation of services related to plastic waste management in cities in developing countries with limited resources. The use of maps that can track plastic waste bins is a recommendation. It will make it easier for garbage services or waste pickers to collect garbage as the map can determine the nearest garbage or bin from the user. Another future work can be giving out incentives to household smart bin users for plastic recycling. Collaboration with supermarkets can be essential as they can give or provide discount coupons based on the weight of plastic items in the bins accumulated in a month.

VIII – LIMITATIONS AND FUTURE LINES OF RESEARCH

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Although all the specific goals were achieved in the course of this thesis, some obstacles were encountered. One of the most relevant ones is the limited access of data in countries where open data is insufficient or not published such as the neighbourhoods mentioned in section 4.2.1. Additionally, there are no existing or former studies that focus on holistic plastic waste management or smart plastic waste management in India or the Philippines which are the two most relevant countries our research focused on.

In this context, the results of the municipal bin placements in the target cities can be unpolished and incomplete as it only determines the number of bins. Future progress in terms of the inclusion of specific areas, for instance, street name or which part of the street the bins should be placed, should be further studied and indicated.

Additionally, a smart bin solely relying on a weight sensor is crucial, especially in times of a sensor malfunction. However, additional sensors can be studied and incorporated while still pursuing one of the main goals, which is maintaining the low cost of the bin. Additionally, according to the Global Alliance of Waste Pickers[17], most organizations of waste pickers are from South America and Asia, thus the availability of waste pickers in other countries can become a handicap. This service does not exist or is limited in other countries; however, volunteer service can be proposed where families or friends of users of the system can be notified at times of collection.

The increase in the number of registered waste pickers can also change the generation of routes that at the moment was done for each waste pickers independently. In that instance, an advanced algorithm that considers overlapping routes can be developed. A larger number of waste pickers would also generate an increase in the number of routes, which can help monitor the traffic state of a city by comparing the actual travel time required to move from one location to another. Also, the proactive waste collection developed in this thesis is reasonable only if the waste generation pace is followed by the users.

Some other future research lines include the use of Open Data as an alternative of sharing analyzed data to the stakeholders and the local community

[17] Global Alliance of Waste Pickers website: https://globalrec.org/

and augmenting knowledge about the accumulation and generation of plastic waste. The collected data from the smart bin can be used to analyze user behaviour such as the number of times they throw plastic waste, the total amount of plastic waste, and other related research fields such as analyzing consumer and recycling behaviour of different types of households. It also can be used for e-health applications as it can determine if the user has any health issues if they have not used the bin for a few days. For example, if the weight sensor is not connected with the application, and if any weight is not registered within a few days, the application can send push notifications in order to ask the user if they are having any issues or if they need any help. If the user does not respond within a few days, the app can send a prompt to the nearest family member or emergency services in order to check in on the user.

IX - REFERENCES

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X - APPENDICES

APPENDIX A: Time Distance Matrices in the Experiments.
This section contains the matrices describing the travel time among the locations in the simulation scenario.

A1: Time distance matrix based on bike displacements. A cell c_{ij} indicates the time required to move from location *i* to *j* in hours:minutes:seconds format.

	wp_1	wp_2	l_1	l_2	l_3	l_4	l_5	l_6	l_7	l_8	DS_1	DS_2	DS_3
wp_1	0:00:00	1:06:00	0:04:00	0:05:00	0:03:00	1:12:00	1:14:00	1:05:00	0:12:00	0:13:00	1:30:00	0:10:00	2:10:00
wp_2	1:06:00	0:00:00	1:06:00	1:12:00	1:07:00	0:10:00	0:12:00	0:05:00	1:06:00	2:12:00	1:30:00	1:13:00	0:25:00
l_1	0:04:00	1:06:00	0:00:00	0:04:00	0:01:00	1:47:00	1:44:00	1:55:00	0:15:00	0:23:00	1:26:00	0:10:00	2:23:00
l_2	0:05:00	1:12:00	0:04:00	0:00:00	0:03:00	1:15:00	1:15:00	1:08:00	0:13:00	0:25:00	1:30:00	0:15:00	2:10:00
l_3	0:03:00	1:07:00	0:01:00	0:03:00	0:00:00	1:10:00	1:12:00	1:03:00	0:15:00	0:17:00	0:54:00	0:15:00	1:13:00
l_4	1:12:00	0:10:00	1:47:00	1:15:00	1:10:00	0:00:00	0:10:00	0:13:00	1:14:00	1:01:00	1:26:00	1:19:00	0:49:00
l_5	1:14:00	0:12:00	1:44:00	1:15:00	1:12:00	0:10:00	0:00:00	0:15:00	1:17:00	1:02:00	1:18:00	2:51:00	0:33:00
l_6	1:05:00	0:05:00	1:55:00	1:08:00	1:03:00	0:13:00	0:15:00	0:00:00	1:08:00	0:55:00	1:34:00	1:12:00	0:28:00
l_7	0:12:00	1:06:00	0:15:00	0:13:00	0:15:00	1:14:00	1:17:00	1:08:00	0:00:00	0:06:00	1:37:00	0:20:00	1:15:00
l_8	0:13:00	2:12:00	0:23:00	0:25:00	0:17:00	1:01:00	1:02:00	0:55:00	0:06:00	0:00:00	1:05:00	0:40:00	1:40:00
DS_1	1:30:00	1:30:00	1:26:00	1:30:00	0:54:00	1:26:00	1:18:00	1:34:00	1:37:00	1:05:00	0:00:00	1:30:00	1:40:00
DS_2	0:10:00	1:13:00	0:10:00	0:15:00	0:15:00	1:19:00	2:51:00	1:12:00	0:20:00	0:40:00	1:30:00	0:00:00	2:30:00
DS_3	2:10:00	0:25:00	2:23:00	2:10:00	1:13:00	0:49:00	0:33:00	0:28:00	1:15:00	1:40:00	1:40:00	2:30:00	0:00:00

A2: Time distance matrix based on walking displacements. A cell c_{ij} indicates the time required to move from location i to j in hours:minutes:seconds format.

	wp_1	wp_2	l_1	l_2	l_3	l_4	l_5	l_6	l_7	l_8	DS_1	DS_2	DS_3
wp_1	0:00:00	2:43:00	0:06:00	0:06:00	0:06:00	2:57:00	3:06:00	2:48:00	0:35:00	0:49:00	1:54:00	0:13:00	3:15:00
wp_2	2:43:00	0:00:00	2:39:00	2:43:00	2:40:00	0:17:00	0:25:00	0:09:00	2:19:00	1:14:00	1:23:00	2:29:00	0:34:00
l_1	0:06:00	2:39:00	0:00:00	0:08:00	0:02:00	2:59:00	3:08:00	2:50:00	0:40:00	0:54:00	1:56:00	0:18:00	3:17:00
l_2	0:06:00	2:43:00	0:08:00	0:00:00	0:07:00	3:04:00	3:12:00	2:54:00	0:41:00	1:02:00	2:00:00	0:19:00	3:10:00
l_3	0:06:00	2:40:00	0:02:00	0:07:00	0:00:00	3:00:00	3:10:00	2:51:00	0:40:00	0:52:00	1:57:00	0:19:00	1:43:00
l_4	2:57:00	0:17:00	2:59:00	3:04:00	3:00:00	0:00:00	0:14:00	0:16:00	2:31:00	2:27:00	1:38:00	2:43:00	1:37:00
l_5	3:06:00	0:25:00	3:08:00	3:12:00	3:10:00	0:14:00	0:00:00	0:21:00	2:43:00	2:34:00	1:34:00	1:20:00	0:45:00
l_6	2:48:00	0:09:00	2:50:00	2:54:00	2:51:00	0:16:00	0:21:00	0:00:00	2:23:00	2:17:00	1:15:00	2:34:00	0:15:00
l_7	0:35:00	2:19:00	0:40:00	0:41:00	0:40:00	2:31:00	2:43:00	2:23:00	0:00:00	0:16:00	1:19:00	0:27:00	2:56:00
l_8	0:49:00	1:14:00	0:54:00	1:02:00	0:52:00	2:27:00	2:34:00	2:17:00	0:16:00	0:00:00	1:31:00	1:02:00	2:49:00
DS_1	1:54:00	1:23:00	1:56:00	2:00:00	1:57:00	1:38:00	1:34:00	1:15:00	1:19:00	1:31:00	0:00:00	1:42:00	1:59:00
DS_2	0:13:00	2:29:00	0:18:00	0:19:00	0:19:00	2:43:00	1:20:00	2:34:00	0:27:00	1:02:00	1:42:00	0:00:00	3:06:00
DS_3	3:15:00	0:34:00	3:17:00	3:10:00	1:43:00	1:37:00	0:45:00	0:15:00	2:56:00	2:49:00	1:59:00	3:06:00	0:00:00

A3: Time distance matrix based on car displacements. A cell c_{ij} indicates the time required to move from location i to j in hours:minutes:seconds format.

	wp_1	wp_2	l_1	l_2	l_3	l_4	l_5	l_6	l_7	l_8	DS_1	DS_2	DS_3
wp_1	0:00:00	0:22:00	0:01:00	0:01:00	0:02:00	0:22:00	0:22:00	0:15:00	0:06:00	0:09:00	0:24:00	0:05:00	0:35:00
wp_2	0:22:00	0:00:00	0:19:00	0:20:00	0:18:00	0:06:00	0:05:00	0:04:00	0:17:00	0:18:00	0:13:00	0:23:00	0:11:00
l_1	0:01:00	0:19:00	0:00:00	0:02:00	0:01:00	0:32:00	0:21:00	0:18:00	0:10:00	0:20:00	0:25:00	0:07:00	0:35:00
l_2	0:01:00	0:20:00	0:02:00	0:00:00	0:02:00	0:35:00	0:35:00	0:30:00	0:06:00	0:20:00	0:27:00	0:07:00	0:35:00
l_3	0:02:00	0:18:00	0:01:00	0:02:00	0:00:00	0:35:00	0:40:00	0:20:00	0:07:00	0:09:00	0:27:00	0:07:00	0:24:00
l_4	0:22:00	0:06:00	0:32:00	0:35:00	0:35:00	0:00:00	0:08:00	0:09:00	0:55:00	0:50:00	0:16:00	0:26:00	0:14:00
l_5	0:22:00	0:05:00	0:21:00	0:35:00	0:40:00	0:08:00	0:00:00	0:06:00	0:55:00	0:50:00	0:17:00	0:28:00	0:16:00
l_6	0:15:00	0:04:00	0:18:00	0:30:00	0:20:00	0:09:00	0:06:00	0:00:00	0:50:00	0:43:00	0:19:00	0:29:00	0:10:00
l_7	0:06:00	0:17:00	0:10:00	0:06:00	0:07:00	0:55:00	0:55:00	0:50:00	0:00:00	0:04:00	0:24:00	0:09:00	0:35:00
l_8	0:09:00	0:18:00	0:20:00	0:20:00	0:09:00	0:50:00	0:50:00	0:43:00	0:04:00	0:00:00	0:23:00	0:11:00	0:34:00
DS_1	0:24:00	0:13:00	0:25:00	0:27:00	0:27:00	0:16:00	0:17:00	0:19:00	0:24:00	0:23:00	0:00:00	0:22:00	0:29:00
DS_2	0:05:00	0:23:00	0:07:00	0:07:00	0:07:00	0:26:00	0:28:00	0:29:00	0:09:00	0:11:00	0:22:00	0:00:00	0:38:00
DS_3	0:35:00	0:11:00	0:35:00	0:35:00	0:24:00	0:14:00	0:16:00	0:10:00	0:35:00	0:34:00	0:29:00	0:38:00	0:00:00

APPENDIX B: Proposed location of the municipal bins in Don Manuel, Quezon City.

1	12 Matimyas Street	14	17 Cordillera Street
2	43 Data Street	15	2 D. Tuazon Street
3	35 Sto Tomas Street	16	7 V. Illustre Street
4	51 Data Street	17	36 Nicanor Ramirez Street
5	21 Data Street	18	19 V. Illustre Street
6	1 Data Street	19	39 V. Illustre Street
7	4 Nicanor Ramirez Street	20	2 Luskot Street
8	4 E. Rodriguez Avenue	21	41 Luskot Street
9	24 E. Rodriguez Avenue	22	51 Lourdes Castillo Street
10	236 E. Rodriguez Avenue	23	27 Lourdes Castillo Street
11	291 E. Rodriguez Avenue	24	11 Lourdes Castillo Street
12	39 Cordillera Street	25	49 Sto Tomas Street
13	52 Cordillera Street	26	11 Sto Tomas Street

APPENDIX C: Time Distance Matrices in the Experiments for Chapter VI.

C1: Matrix for collection by Car

	SB1	SB2	SB3	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	WP1	DS2
SB1	0:00:00	0:02:00	0:01:00	0:01:00	0:01:00	0:01:00	0:02:00	0:01:00	0:01:00	0:02:00	0:01:00	0:01:00	0:01:00	0:01:00	0:05:00	0:02:00	0:02:00	0:02:00	0:02:00	0:01:00	0:02:00	0:03:00	0:01:00	0:02:00	0:03:00	0:01:00	0:01:00	0:01:00	0:01:00	0:01:00	0:05:00
SB2	0:02:00	0:00:00	0:02:00	0:01:00	0:02:00	0:02:00	0:02:00	0:02:00	0:02:00	0:02:00	0:03:00	0:02:00	0:03:00	0:02:00	0:01:00	0:01:00	0:01:00	0:01:00	0:01:00	0:01:00	0:01:00	0:01:00	0:02:00	0:02:00	0:02:00	0:01:00	0:02:00	0:02:00	0:03:00	0:02:00	0:05:00
SB3	0:01:00	0:02:00	0:00:00	0:01:00	0:00:00	0:01:00	0:02:00	0:01:00	0:01:00	0:02:00	0:01:00	0:01:00	0:01:00	0:01:00	0:05:00	0:02:00	0:02:00	0:02:00	0:02:00	0:01:00	0:02:00	0:03:00	0:01:00	0:02:00	0:03:00	0:01:00	0:01:00	0:01:00	0:01:00	0:01:00	0:05:00
1	0:01:00	0:01:00	0:01:00	0:00:00	0:01:00	0:01:00	0:02:00	0:01:00	0:01:00	0:02:00	0:01:00	0:01:00	0:01:00	0:01:00	0:05:00	0:02:00	0:02:00	0:02:00	0:02:00	0:01:00	0:02:00	0:03:00	0:01:00	0:02:00	0:03:00	0:01:00	0:01:00	0:01:00	0:01:00	0:01:00	0:04:00
2	0:01:00	0:02:00	0:02:00	0:02:00	0:00:00	0:01:00	0:02:00	0:01:00	0:01:00	0:02:00	0:01:00	0:01:00	0:01:00	0:01:00	0:05:00	0:02:00	0:02:00	0:02:00	0:02:00	0:01:00	0:02:00	0:03:00	0:01:00	0:02:00	0:03:00	0:01:00	0:01:00	0:01:00	0:01:00	0:01:00	0:07:00
3	0:01:00	0:02:00	0:01:00	0:01:00	0:01:00	0:00:00	0:02:00	0:01:00	0:01:00	0:02:00	0:01:00	0:01:00	0:01:00	0:01:00	0:05:00	0:02:00	0:02:00	0:02:00	0:02:00	0:01:00	0:02:00	0:03:00	0:01:00	0:02:00	0:03:00	0:01:00	0:01:00	0:01:00	0:01:00	0:01:00	0:03:00
4	0:02:00	0:02:00	0:01:00	0:02:00	0:01:00	0:02:00	0:00:00	0:03:00	0:03:00	0:04:00	0:02:00	0:02:00	0:02:00	0:02:00	0:01:00	0:01:00	0:01:00	0:01:00	0:02:00	0:03:00	0:02:00	0:02:00	0:02:00	0:02:00	0:01:00	0:01:00	0:03:00	0:01:00	0:03:00	0:01:00	0:05:00
5	0:01:00	0:02:00	0:01:00	0:01:00	0:01:00	0:02:00	0:03:00	0:00:00	0:01:00	0:01:00	0:01:00	0:01:00	0:02:00	0:02:00	0:01:00	0:01:00	0:01:00	0:01:00	0:02:00	0:03:00	0:02:00	0:02:00	0:02:00	0:02:00	0:01:00	0:01:00	0:03:00	0:01:00	0:03:00	0:02:00	0:04:00
6	0:01:00	0:02:00	0:01:00	0:01:00	0:01:00	0:02:00	0:03:00	0:01:00	0:00:00	0:01:00	0:01:00	0:01:00	0:01:00	0:02:00	0:02:00	0:02:00	0:01:00	0:02:00	0:02:00	0:01:00	0:02:00	0:02:00	0:01:00	0:01:00	0:01:00	0:01:00	0:01:00	0:03:00	0:03:00	0:02:00	0:05:00
7	0:02:00	0:02:00	0:03:00	0:02:00	0:03:00	0:02:00	0:04:00	0:01:00	0:01:00	0:00:00	0:02:00	0:02:00	0:02:00	0:02:00	0:01:00	0:01:00	0:01:00	0:01:00	0:02:00	0:03:00	0:02:00	0:02:00	0:02:00	0:02:00	0:01:00	0:01:00	0:03:00	0:01:00	0:03:00	0:02:00	0:06:00
8	0:01:00	0:03:00	0:02:00	0:01:00	0:02:00	0:03:00	0:02:00	0:01:00	0:01:00	0:02:00	0:00:00	0:01:00	0:01:00	0:03:00	0:02:00	0:01:00	0:01:00	0:01:00	0:02:00	0:02:00	0:02:00	0:01:00	0:02:00	0:02:00	0:03:00	0:02:00	0:02:00	0:02:00	0:01:00	0:02:00	0:06:00
9	0:01:00	0:02:00	0:01:00	0:01:00	0:01:00	0:02:00	0:02:00	0:01:00	0:01:00	0:02:00	0:01:00	0:00:00	0:02:00	0:02:00	0:01:00	0:01:00	0:01:00	0:01:00	0:02:00	0:03:00	0:02:00	0:02:00	0:02:00	0:02:00	0:01:00	0:01:00	0:03:00	0:01:00	0:03:00	0:02:00	0:06:00
10	0:01:00	0:03:00	0:01:00	0:01:00	0:01:00	0:02:00	0:02:00	0:02:00	0:01:00	0:02:00	0:01:00	0:02:00	0:00:00	0:02:00	0:02:00	0:01:00	0:02:00	0:02:00	0:01:00	0:02:00	0:02:00	0:01:00	0:01:00	0:01:00	0:01:00	0:01:00	0:02:00	0:03:00	0:02:00	0:02:00	0:03:00
11	0:01:00	0:02:00	0:01:00	0:01:00	0:01:00	0:00:00	0:02:00	0:02:00	0:02:00	0:02:00	0:03:00	0:02:00	0:02:00	0:00:00	0:02:00	0:01:00	0:01:00	0:01:00	0:01:00	0:02:00	0:03:00	0:02:00	0:02:00	0:02:00	0:02:00	0:01:00	0:01:00	0:03:00	0:02:00	0:01:00	0:04:00
12	0:05:00	0:01:00	0:02:00	0:01:00	0:02:00	0:02:00	0:01:00	0:01:00	0:02:00	0:01:00	0:02:00	0:01:00	0:02:00	0:02:00	0:00:00	0:01:00	0:01:00	0:02:00	0:02:00	0:01:00	0:02:00	0:02:00	0:01:00	0:01:00	0:01:00	0:01:00	0:01:00	0:03:00	0:03:00	0:02:00	0:05:00
13	0:02:00	0:01:00	0:02:00	0:02:00	0:02:00	0:01:00	0:01:00	0:01:00	0:02:00	0:01:00	0:01:00	0:01:00	0:01:00	0:01:00	0:01:00	0:00:00	0:01:00	0:01:00	0:01:00	0:01:00	0:01:00	0:01:00	0:02:00	0:02:00	0:02:00	0:01:00	0:02:00	0:02:00	0:03:00	0:02:00	0:07:00
14	0:02:00	0:01:00	0:02:00	0:02:00	0:02:00	0:01:00	0:01:00	0:01:00	0:01:00	0:01:00	0:01:00	0:01:00	0:02:00	0:01:00	0:01:00	0:01:00	0:00:00	0:02:00	0:02:00	0:01:00	0:02:00	0:02:00	0:01:00	0:01:00	0:01:00	0:01:00	0:01:00	0:03:00	0:03:00	0:02:00	0:06:00
15	0:02:00	0:01:00	0:01:00	0:01:00	0:01:00	0:01:00	0:01:00	0:01:00	0:02:00	0:01:00	0:01:00	0:01:00	0:02:00	0:01:00	0:02:00	0:01:00	0:02:00	0:00:00	0:01:00	0:01:00	0:01:00	0:01:00	0:02:00	0:03:00	0:02:00	0:03:00	0:02:00	0:02:00	0:02:00	0:02:00	0:06:00
16	0:02:00	0:01:00	0:02:00	0:02:00	0:02:00	0:01:00	0:02:00	0:02:00	0:02:00	0:02:00	0:02:00	0:02:00	0:01:00	0:01:00	0:02:00	0:01:00	0:02:00	0:01:00	0:00:00	0:03:00	0:02:00	0:02:00	0:02:00	0:02:00	0:01:00	0:01:00	0:03:00	0:02:00	0:01:00	0:02:00	0:07:00
17	0:01:00	0:01:00	0:02:00	0:02:00	0:02:00	0:02:00	0:03:00	0:03:00	0:01:00	0:03:00	0:02:00	0:03:00	0:02:00	0:02:00	0:01:00	0:01:00	0:01:00	0:01:00	0:03:00	0:00:00	0:02:00	0:02:00	0:01:00	0:02:00	0:02:00	0:01:00	0:01:00	0:01:00	0:01:00	0:01:00	0:05:00
18	0:02:00	0:01:00	0:01:00	0:01:00	0:01:00	0:03:00	0:02:00	0:02:00	0:02:00	0:02:00	0:02:00	0:02:00	0:02:00	0:03:00	0:02:00	0:01:00	0:02:00	0:01:00	0:02:00	0:02:00	0:00:00	0:01:00	0:01:00	0:01:00	0:01:00	0:01:00	0:02:00	0:01:00	0:03:00	0:02:00	0:07:00
19	0:03:00	0:01:00	0:02:00	0:02:00	0:02:00	0:02:00	0:02:00	0:02:00	0:02:00	0:02:00	0:01:00	0:02:00	0:01:00	0:02:00	0:02:00	0:01:00	0:02:00	0:01:00	0:02:00	0:02:00	0:01:00	0:00:00	0:02:00	0:01:00	0:01:00	0:01:00	0:02:00	0:02:00	0:03:00	0:01:00	0:05:00
20	0:01:00	0:02:00	0:02:00	0:02:00	0:02:00	0:02:00	0:02:00	0:02:00	0:01:00	0:02:00	0:02:00	0:02:00	0:01:00	0:02:00	0:01:00	0:02:00	0:01:00	0:02:00	0:02:00	0:01:00	0:01:00	0:02:00	0:00:00	0:01:00	0:02:00	0:01:00	0:01:00	0:02:00	0:01:00	0:03:00	0:03:00
21	0:02:00	0:02:00	0:01:00	0:01:00	0:01:00	0:02:00	0:02:00	0:02:00	0:01:00	0:02:00	0:02:00	0:02:00	0:01:00	0:02:00	0:01:00	0:02:00	0:01:00	0:03:00	0:02:00	0:02:00	0:01:00	0:01:00	0:01:00	0:00:00	0:01:00	0:01:00	0:02:00	0:02:00	0:03:00	0:01:00	0:05:00
22	0:03:00	0:02:00	0:01:00	0:01:00	0:01:00	0:02:00	0:01:00	0:01:00	0:01:00	0:01:00	0:03:00	0:01:00	0:01:00	0:02:00	0:01:00	0:02:00	0:01:00	0:02:00	0:01:00	0:02:00	0:01:00	0:01:00	0:02:00	0:01:00	0:00:00	0:01:00	0:01:00	0:02:00	0:04:00	0:01:00	0:07:00
23	0:01:00	0:01:00	0:01:00	0:01:00	0:01:00	0:01:00	0:01:00	0:01:00	0:01:00	0:01:00	0:02:00	0:01:00	0:01:00	0:01:00	0:01:00	0:01:00	0:01:00	0:03:00	0:01:00	0:01:00	0:01:00	0:01:00	0:01:00	0:01:00	0:01:00	0:00:00	0:01:00	0:01:00	0:02:00	0:02:00	0:05:00
24	0:01:00	0:02:00	0:01:00	0:01:00	0:01:00	0:01:00	0:03:00	0:03:00	0:01:00	0:03:00	0:02:00	0:03:00	0:02:00	0:01:00	0:01:00	0:02:00	0:01:00	0:02:00	0:03:00	0:01:00	0:02:00	0:02:00	0:01:00	0:02:00	0:01:00	0:01:00	0:00:00	0:02:00	0:02:00	0:03:00	0:06:00
25	0:01:00	0:02:00	0:01:00	0:01:00	0:01:00	0:03:00	0:01:00	0:01:00	0:03:00	0:01:00	0:02:00	0:01:00	0:03:00	0:03:00	0:03:00	0:02:00	0:03:00	0:02:00	0:02:00	0:01:00	0:01:00	0:02:00	0:02:00	0:02:00	0:02:00	0:01:00	0:02:00	0:00:00	0:03:00	0:01:00	0:05:00
26	0:01:00	0:03:00	0:03:00	0:03:00	0:03:00	0:02:00	0:03:00	0:03:00	0:03:00	0:03:00	0:01:00	0:03:00	0:02:00	0:02:00	0:03:00	0:03:00	0:03:00	0:02:00	0:01:00	0:01:00	0:03:00	0:03:00	0:01:00	0:03:00	0:04:00	0:02:00	0:02:00	0:03:00	0:00:00	0:03:00	0:06:00
WP1	0:01:00	0:02:00	0:02:00	0:02:00	0:02:00	0:01:00	0:01:00	0:02:00	0:02:00	0:02:00	0:02:00	0:02:00	0:02:00	0:01:00	0:02:00	0:02:00	0:02:00	0:02:00	0:02:00	0:01:00	0:02:00	0:01:00	0:03:00	0:01:00	0:01:00	0:02:00	0:03:00	0:01:00	0:03:00	0:00:00	0:07:00
DS2	0:05:00	0:05:00	0:05:00	0:04:00	0:07:00	0:03:00	0:05:00	0:04:00	0:05:00	0:06:00	0:06:00	0:06:00	0:03:00	0:04:00	0:05:00	0:07:00	0:06:00	0:06:00	0:07:00	0:05:00	0:07:00	0:05:00	0:03:00	0:05:00	0:07:00	0:05:00	0:06:00	0:05:00	0:06:00	0:07:00	0:00:00

C2: Matrix for collection on Foot

	SB1	SB2	SB3	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	WP1	DS2
SB1	0:00:00	0:07:00	0:03:00	0:01:00	0:03:00	0:07:00	0:05:00	0:02:00	0:03:00	0:04:00	0:03:00	0:01:00	0:03:00	0:07:00	0:06:00	0:09:00	0:07:00	0:05:00	0:01:00	0:04:00	0:05:00	0:07:00	0:04:00	0:06:00	0:06:00	0:04:00	0:02:00	0:03:00	0:03:00	0:06:00	0:27:00
SB2	0:07:00	0:00:00	0:05:00	0:06:00	0:05:00	0:09:00	0:07:00	0:06:00	0:07:00	0:08:00	0:10:00	0:08:00	0:10:00	0:09:00	0:05:00	0:06:00	0:02:00	0:02:00	0:03:00	0:05:00	0:03:00	0:03:00	0:05:00	0:05:00	0:05:00	0:04:00	0:05:00	0:07:00	0:10:00	0:06:00	0:30:00
SB3	0:03:00	0:05:00	0:00:00	0:01:00	0:03:00	0:05:00	0:02:00	0:01:00	0:03:00	0:08:00	0:06:00	0:04:00	0:03:00	0:05:00	0:04:00	0:05:00	0:06:00	0:03:00	0:04:00	0:04:00	0:03:00	0:05:00	0:03:00	0:04:00	0:03:00	0:01:00	0:02:00	0:02:00	0:05:00	0:07:00	0:26:00
1	0:01:00	0:06:00	0:01:00	0:00:00	0:01:00	0:02:00	0:05:00	0:02:00	0:03:00	0:04:00	0:03:00	0:01:00	0:03:00	0:07:00	0:06:00	0:09:00	0:07:00	0:05:00	0:01:00	0:04:00	0:05:00	0:07:00	0:04:00	0:06:00	0:06:00	0:04:00	0:02:00	0:03:00	0:03:00	0:06:00	0:24:00
2	0:03:00	0:05:00	0:03:00	0:03:00	0:00:00	0:01:00	0:07:00	0:06:00	0:07:00	0:08:00	0:10:00	0:08:00	0:10:00	0:09:00	0:05:00	0:06:00	0:02:00	0:02:00	0:03:00	0:05:00	0:03:00	0:03:00	0:05:00	0:05:00	0:05:00	0:04:00	0:05:00	0:07:00	0:10:00	0:06:00	0:26:00
3	0:07:00	0:09:00	0:05:00	0:02:00	0:01:00	0:00:00	0:02:00	0:01:00	0:03:00	0:08:00	0:06:00	0:04:00	0:03:00	0:05:00	0:04:00	0:05:00	0:06:00	0:03:00	0:04:00	0:04:00	0:03:00	0:05:00	0:03:00	0:04:00	0:03:00	0:01:00	0:02:00	0:02:00	0:05:00	0:07:00	0:26:00
4	0:05:00	0:07:00	0:02:00	0:03:00	0:02:00	0:06:00	0:00:00	0:03:00	0:05:00	0:09:00	0:07:00	0:05:00	0:05:00	0:06:00	0:02:00	0:03:00	0:04:00	0:04:00	0:06:00	0:05:00	0:04:00	0:05:00	0:05:00	0:05:00	0:04:00	0:03:00	0:04:00	0:04:00	0:07:00	0:03:00	0:23:00
5	0:02:00	0:06:00	0:01:00	0:01:00	0:01:00	0:06:00	0:03:00	0:00:00	0:02:00	0:04:00	0:06:00	0:03:00	0:05:00	0:06:00	0:02:00	0:03:00	0:04:00	0:04:00	0:06:00	0:05:00	0:04:00	0:05:00	0:05:00	0:05:00	0:04:00	0:03:00	0:04:00	0:04:00	0:07:00	0:03:00	0:28:00
6	0:03:00	0:07:00	0:03:00	0:02:00	0:03:00	0:03:00	0:05:00	0:02:00	0:00:00	0:02:00	0:04:00	0:04:00	0:06:00	0:03:00	0:05:00	0:04:00	0:05:00	0:06:00	0:03:00	0:04:00	0:04:00	0:03:00	0:05:00	0:03:00	0:04:00	0:03:00	0:01:00	0:02:00	0:02:00	0:05:00	0:30:00
7	0:04:00	0:08:00	0:08:00	0:05:00	0:08:00	0:04:00	0:09:00	0:04:00	0:02:00	0:00:00	0:06:00	0:02:00	0:03:00	0:04:00	0:04:00	0:06:00	0:05:00	0:04:00	0:05:00	0:05:00	0:05:00	0:04:00	0:03:00	0:04:00	0:04:00	0:06:00	0:05:00	0:04:00	0:05:00	0:05:00	0:30:00
8	0:03:00	0:10:00	0:06:00	0:04:00	0:06:00	0:03:00	0:07:00	0:06:00	0:04:00	0:06:00	0:00:00	0:05:00	0:06:00	0:03:00	0:04:00	0:04:00	0:03:00	0:05:00	0:04:00	0:04:00	0:03:00	0:05:00	0:03:00	0:04:00	0:03:00	0:01:00	0:04:00	0:03:00	0:05:00	0:03:00	0:30:00
9	0:01:00	0:08:00	0:04:00	0:02:00	0:04:00	0:05:00	0:05:00	0:03:00	0:04:00	0:02:00	0:05:00	0:00:00	0:06:00	0:05:00	0:04:00	0:05:00	0:05:00	0:05:00	0:04:00	0:03:00	0:04:00	0:04:00	0:04:00	0:03:00	0:01:00	0:04:00	0:03:00	0:01:00	0:02:00	0:02:00	0:28:00
10	0:03:00	0:10:00	0:03:00	0:04:00	0:03:00	0:05:00	0:05:00	0:05:00	0:06:00	0:03:00	0:06:00	0:06:00	0:00:00	0:05:00	0:04:00	0:05:00	0:05:00	0:05:00	0:04:00	0:03:00	0:04:00	0:04:00	0:04:00	0:03:00	0:01:00	0:04:00	0:03:00	0:01:00	0:02:00	0:02:00	0:27:00
11	0:07:00	0:09:00	0:05:00	0:05:00	0:05:00	0:00:00	0:06:00	0:06:00	0:03:00	0:04:00	0:03:00	0:05:00	0:05:00	0:00:00	0:04:00	0:04:00	0:03:00	0:05:00	0:04:00	0:04:00	0:03:00	0:05:00	0:03:00	0:04:00	0:03:00	0:01:00	0:04:00	0:03:00	0:05:00	0:03:00	0:23:00
12	0:06:00	0:05:00	0:04:00	0:04:00	0:04:00	0:04:00	0:02:00	0:02:00	0:05:00	0:04:00	0:04:00	0:04:00	0:04:00	0:04:00	0:00:00	0:05:00	0:06:00	0:03:00	0:04:00	0:04:00	0:03:00	0:05:00	0:03:00	0:04:00	0:03:00	0:01:00	0:02:00	0:02:00	0:05:00	0:07:00	0:23:00
13	0:09:00	0:06:00	0:05:00	0:03:00	0:05:00	0:04:00	0:03:00	0:03:00	0:04:00	0:06:00	0:04:00	0:05:00	0:05:00	0:04:00	0:05:00	0:00:00	0:06:00	0:07:00	0:08:00	0:10:00	0:08:00	0:10:00	0:09:00	0:05:00	0:06:00	0:02:00	0:02:00	0:03:00	0:05:00	0:03:00	0:23:00
14	0:07:00	0:02:00	0:06:00	0:04:00	0:06:00	0:03:00	0:04:00	0:04:00	0:05:00	0:05:00	0:03:00	0:05:00	0:05:00	0:03:00	0:06:00	0:06:00	0:00:00	0:05:00	0:04:00	0:04:00	0:03:00	0:05:00	0:03:00	0:04:00	0:03:00	0:01:00	0:04:00	0:03:00	0:05:00	0:03:00	0:31:00
15	0:05:00	0:02:00	0:03:00	0:04:00	0:03:00	0:05:00	0:04:00	0:04:00	0:06:00	0:04:00	0:05:00	0:05:00	0:05:00	0:05:00	0:03:00	0:07:00	0:05:00	0:00:00	0:04:00	0:04:00	0:03:00	0:05:00	0:03:00	0:04:00	0:03:00	0:01:00	0:04:00	0:03:00	0:05:00	0:03:00	0:34:00
16	0:01:00	0:03:00	0:04:00	0:03:00	0:04:00	0:04:00	0:06:00	0:06:00	0:03:00	0:05:00	0:04:00	0:04:00	0:04:00	0:04:00	0:04:00	0:08:00	0:04:00	0:04:00	0:00:00	0:04:00	0:03:00	0:05:00	0:03:00	0:04:00	0:03:00	0:01:00	0:02:00	0:02:00	0:05:00	0:07:00	0:27:00
17	0:04:00	0:05:00	0:04:00	0:05:00	0:04:00	0:04:00	0:05:00	0:05:00	0:04:00	0:05:00	0:04:00	0:03:00	0:03:00	0:04:00	0:04:00	0:10:00	0:04:00	0:04:00	0:04:00	0:00:00	0:03:00	0:05:00	0:03:00	0:04:00	0:03:00	0:01:00	0:04:00	0:03:00	0:05:00	0:03:00	0:34:00
18	0:05:00	0:03:00	0:03:00	0:03:00	0:03:00	0:03:00	0:04:00	0:04:00	0:04:00	0:05:00	0:03:00	0:04:00	0:04:00	0:03:00	0:03:00	0:08:00	0:03:00	0:03:00	0:03:00	0:03:00	0:00:00	0:02:00	0:02:00	0:03:00	0:04:00	0:02:00	0:03:00	0:05:00	0:07:00	0:08:00	0:23:00
19	0:07:00	0:03:00	0:05:00	0:05:00	0:05:00	0:05:00	0:05:00	0:05:00	0:03:00	0:04:00	0:05:00	0:04:00	0:04:00	0:05:00	0:05:00	0:10:00	0:05:00	0:05:00	0:05:00	0:05:00	0:02:00	0:00:00	0:04:00	0:03:00	0:04:00	0:03:00	0:05:00	0:07:00	0:09:00	0:05:00	0:27:00
20	0:04:00	0:05:00	0:03:00	0:03:00	0:03:00	0:03:00	0:05:00	0:05:00	0:05:00	0:03:00	0:03:00	0:04:00	0:04:00	0:03:00	0:03:00	0:09:00	0:03:00	0:03:00	0:03:00	0:03:00	0:02:00	0:04:00	0:00:00	0:03:00	0:04:00	0:02:00	0:01:00	0:06:00	0:04:00	0:08:00	0:34:00
21	0:06:00	0:05:00	0:04:00	0:04:00	0:04:00	0:04:00	0:05:00	0:05:00	0:03:00	0:04:00	0:04:00	0:03:00	0:03:00	0:04:00	0:04:00	0:05:00	0:04:00	0:04:00	0:04:00	0:04:00	0:03:00	0:03:00	0:03:00	0:00:00	0:03:00	0:02:00	0:04:00	0:06:00	0:08:00	0:05:00	0:23:00
22	0:06:00	0:05:00	0:03:00	0:03:00	0:03:00	0:03:00	0:04:00	0:04:00	0:04:00	0:04:00	0:03:00	0:01:00	0:01:00	0:03:00	0:03:00	0:06:00	0:03:00	0:03:00	0:03:00	0:03:00	0:04:00	0:04:00	0:04:00	0:03:00	0:00:00	0:02:00	0:03:00	0:05:00	0:08:00	0:04:00	0:31:00
23	0:04:00	0:04:00	0:01:00	0:01:00	0:01:00	0:01:00	0:03:00	0:03:00	0:03:00	0:06:00	0:01:00	0:04:00	0:04:00	0:01:00	0:01:00	0:02:00	0:01:00	0:01:00	0:01:00	0:01:00	0:02:00	0:03:00	0:02:00	0:02:00	0:02:00	0:00:00	0:02:00	0:03:00	0:05:00	0:07:00	0:27:00
24	0:02:00	0:05:00	0:02:00	0:02:00	0:02:00	0:04:00	0:04:00	0:04:00	0:01:00	0:05:00	0:04:00	0:03:00	0:03:00	0:04:00	0:02:00	0:02:00	0:04:00	0:04:00	0:02:00	0:04:00	0:03:00	0:05:00	0:01:00	0:04:00	0:03:00	0:02:00	0:00:00	0:04:00	0:04:00	0:08:00	0:23:00
25	0:03:00	0:07:00	0:02:00	0:02:00	0:02:00	0:03:00	0:04:00	0:04:00	0:02:00	0:04:00	0:03:00	0:01:00	0:01:00	0:03:00	0:02:00	0:03:00	0:03:00	0:03:00	0:02:00	0:03:00	0:05:00	0:07:00	0:06:00	0:06:00	0:05:00	0:03:00	0:04:00	0:00:00	0:05:00	0:03:00	0:34:00
26	0:03:00	0:10:00	0:05:00	0:05:00	0:05:00	0:05:00	0:07:00	0:07:00	0:02:00	0:05:00	0:05:00	0:02:00	0:02:00	0:05:00	0:05:00	0:05:00	0:05:00	0:05:00	0:05:00	0:05:00	0:07:00	0:09:00	0:04:00	0:08:00	0:08:00	0:05:00	0:04:00	0:05:00	0:00:00	0:10:00	0:27:00
WP1	0:06:00	0:06:00	0:07:00	0:07:00	0:07:00	0:03:00	0:03:00	0:03:00	0:05:00	0:05:00	0:03:00	0:02:00	0:02:00	0:03:00	0:07:00	0:03:00	0:03:00	0:03:00	0:07:00	0:03:00	0:08:00	0:05:00	0:08:00	0:05:00	0:04:00	0:07:00	0:08:00	0:03:00	0:10:00	0:00:00	0:23:00
DS2	0:27:00	0:30:00	0:26:00	0:24:00	0:26:00	0:26:00	0:23:00	0:28:00	0:30:00	0:30:00	0:30:00	0:28:00	0:27:00	0:23:00	0:23:00	0:23:00	0:31:00	0:34:00	0:27:00	0:34:00	0:23:00	0:27:00	0:34:00	0:23:00	0:31:00	0:27:00	0:23:00	0:34:00	0:27:00	0:23:00	0:00:00

C3: Matrix for collection by Bike

	SB1	SB2	SB3	1	2	3	4	5	6	7	8	9	10	11
SB1	0:00:00	0:07:00	0:03:00	0:01:00	0:03:00	0:07:00	0:05:00	0:02:00	0:03:00	0:04:00	0:03:00	0:01:00	0:03:00	0:07:00
SB2	0:07:00	0:00:00	0:05:00	0:03:00	0:05:00	0:09:00	0:07:00	0:06:00	0:07:00	0:08:00	0:10:00	0:08:00	0:10:00	0:09:00
SB3	0:03:00	0:05:00	0:00:00	0:01:00	0:01:00	0:05:00	0:02:00	0:01:00	0:03:00	0:08:00	0:06:00	0:04:00	0:03:00	0:05:00
1	0:01:00	0:03:00	0:01:00	0:00:00	0:02:00	0:01:00	0:02:00	0:01:00	0:01:00	0:04:00	0:03:00	0:01:00	0:03:00	0:04:00
2	0:03:00	0:05:00	0:01:00	0:02:00	0:00:00	0:02:00	0:02:00	0:01:00	0:03:00	0:08:00	0:06:00	0:04:00	0:03:00	0:05:00
3	0:07:00	0:09:00	0:05:00	0:01:00	0:02:00	0:00:00	0:06:00	0:06:00	0:03:00	0:04:00	0:03:00	0:05:00	0:05:00	0:00:00
4	0:05:00	0:07:00	0:02:00	0:02:00	0:02:00	0:06:00	0:00:00	0:03:00	0:05:00	0:09:00	0:07:00	0:05:00	0:05:00	0:06:00
5	0:02:00	0:06:00	0:01:00	0:01:00	0:01:00	0:06:00	0:03:00	0:00:00	0:02:00	0:04:00	0:06:00	0:03:00	0:05:00	0:06:00
6	0:03:00	0:07:00	0:03:00	0:01:00	0:03:00	0:03:00	0:05:00	0:02:00	0:00:00	0:02:00	0:04:00	0:04:00	0:06:00	0:03:00
7	0:04:00	0:08:00	0:08:00	0:04:00	0:08:00	0:04:00	0:09:00	0:04:00	0:02:00	0:00:00	0:06:00	0:02:00	0:03:00	0:04:00
8	0:03:00	0:10:00	0:06:00	0:03:00	0:06:00	0:03:00	0:07:00	0:06:00	0:04:00	0:06:00	0:00:00	0:05:00	0:06:00	0:03:00
9	0:01:00	0:08:00	0:04:00	0:01:00	0:04:00	0:05:00	0:05:00	0:03:00	0:04:00	0:02:00	0:05:00	0:00:00	0:06:00	0:05:00
10	0:03:00	0:10:00	0:03:00	0:03:00	0:03:00	0:05:00	0:05:00	0:05:00	0:06:00	0:03:00	0:06:00	0:06:00	0:00:00	0:05:00
11	0:07:00	0:09:00	0:05:00	0:04:00	0:05:00	0:00:00	0:06:00	0:06:00	0:03:00	0:04:00	0:03:00	0:05:00	0:05:00	0:00:00
12	0:06:00	0:05:00	0:04:00	0:03:00	0:04:00	0:04:00	0:02:00	0:02:00	0:05:00	0:04:00	0:04:00	0:04:00	0:04:00	0:04:00
13	0:09:00	0:06:00	0:05:00	0:04:00	0:05:00	0:04:00	0:03:00	0:03:00	0:04:00	0:06:00	0:04:00	0:05:00	0:05:00	0:04:00
14	0:07:00	0:02:00	0:06:00	0:03:00	0:06:00	0:03:00	0:04:00	0:04:00	0:05:00	0:05:00	0:03:00	0:05:00	0:05:00	0:03:00
15	0:05:00	0:02:00	0:03:00	0:05:00	0:03:00	0:05:00	0:04:00	0:04:00	0:06:00	0:04:00	0:05:00	0:05:00	0:05:00	0:05:00
16	0:01:00	0:03:00	0:04:00	0:03:00	0:04:00	0:04:00	0:06:00	0:06:00	0:03:00	0:05:00	0:04:00	0:04:00	0:04:00	0:04:00
17	0:04:00	0:05:00	0:04:00	0:04:00	0:04:00	0:04:00	0:05:00	0:05:00	0:04:00	0:05:00	0:04:00	0:03:00	0:03:00	0:04:00
18	0:05:00	0:03:00	0:03:00	0:03:00	0:03:00	0:03:00	0:04:00	0:04:00	0:04:00	0:05:00	0:03:00	0:04:00	0:04:00	0:03:00
19	0:07:00	0:03:00	0:05:00	0:01:00	0:05:00	0:05:00	0:05:00	0:05:00	0:03:00	0:04:00	0:05:00	0:04:00	0:04:00	0:05:00
20	0:04:00	0:05:00	0:03:00	0:02:00	0:03:00	0:03:00	0:05:00	0:05:00	0:05:00	0:03:00	0:03:00	0:04:00	0:04:00	0:03:00
21	0:06:00	0:05:00	0:04:00	0:02:00	0:04:00	0:04:00	0:05:00	0:05:00	0:03:00	0:04:00	0:04:00	0:03:00	0:03:00	0:04:00
22	0:06:00	0:05:00	0:03:00	0:03:00	0:03:00	0:03:00	0:04:00	0:04:00	0:04:00	0:04:00	0:03:00	0:01:00	0:01:00	0:03:00
23	0:04:00	0:04:00	0:01:00	0:01:00	0:01:00	0:01:00	0:03:00	0:03:00	0:03:00	0:06:00	0:01:00	0:04:00	0:04:00	0:01:00
24	0:02:00	0:05:00	0:02:00	0:02:00	0:02:00	0:04:00	0:04:00	0:04:00	0:01:00	0:05:00	0:04:00	0:03:00	0:03:00	0:04:00
25	0:03:00	0:07:00	0:02:00	0:02:00	0:02:00	0:03:00	0:04:00	0:04:00	0:02:00	0:04:00	0:03:00	0:01:00	0:01:00	0:03:00
26	0:03:00	0:10:00	0:05:00	0:05:00	0:05:00	0:05:00	0:07:00	0:07:00	0:02:00	0:05:00	0:05:00	0:02:00	0:02:00	0:05:00
WP1	0:06:00	0:06:00	0:07:00	0:07:00	0:07:00	0:03:00	0:03:00	0:03:00	0:05:00	0:05:00	0:03:00	0:02:00	0:02:00	0:03:00
DS2	0:24:00	0:24:00	0:26:00	0:24:00	0:24:00	0:20:00	0:20:00	0:23:00	0:23:00	0:20:00	0:23:00	0:20:00	0:20:00	0:21:00

	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	WP1	DS2
SB1	0:06:00	0:09:00	0:07:00	0:05:00	0:01:00	0:04:00	0:05:00	0:07:00	0:04:00	0:06:00	0:06:00	0:04:00	0:02:00	0:03:00	0:03:00	0:06:00	0:24:00
SB2	0:05:00	0:06:00	0:02:00	0:02:00	0:03:00	0:05:00	0:03:00	0:03:00	0:05:00	0:05:00	0:05:00	0:04:00	0:05:00	0:07:00	0:10:00	0:06:00	0:24:00
SB3	0:04:00	0:05:00	0:06:00	0:03:00	0:04:00	0:04:00	0:03:00	0:05:00	0:03:00	0:04:00	0:03:00	0:01:00	0:02:00	0:02:00	0:05:00	0:07:00	0:26:00
1	0:03:00	0:04:00	0:03:00	0:05:00	0:03:00	0:04:00	0:03:00	0:01:00	0:02:00	0:02:00	0:03:00	0:01:00	0:02:00	0:02:00	0:05:00	0:07:00	0:24:00
2	0:04:00	0:05:00	0:06:00	0:03:00	0:04:00	0:04:00	0:03:00	0:05:00	0:03:00	0:04:00	0:03:00	0:01:00	0:02:00	0:02:00	0:05:00	0:07:00	0:24:00
3	0:04:00	0:04:00	0:03:00	0:05:00	0:04:00	0:04:00	0:03:00	0:05:00	0:03:00	0:04:00	0:03:00	0:01:00	0:04:00	0:03:00	0:05:00	0:03:00	0:20:00
4	0:02:00	0:03:00	0:04:00	0:04:00	0:06:00	0:05:00	0:04:00	0:05:00	0:05:00	0:05:00	0:04:00	0:03:00	0:04:00	0:04:00	0:07:00	0:03:00	0:20:00
5	0:02:00	0:03:00	0:04:00	0:04:00	0:06:00	0:05:00	0:04:00	0:05:00	0:05:00	0:05:00	0:04:00	0:03:00	0:04:00	0:04:00	0:07:00	0:03:00	0:23:00
6	0:05:00	0:04:00	0:05:00	0:06:00	0:03:00	0:04:00	0:04:00	0:03:00	0:05:00	0:03:00	0:04:00	0:03:00	0:01:00	0:02:00	0:02:00	0:05:00	0:23:00
7	0:04:00	0:06:00	0:05:00	0:04:00	0:05:00	0:05:00	0:05:00	0:04:00	0:03:00	0:04:00	0:04:00	0:06:00	0:05:00	0:04:00	0:05:00	0:05:00	0:20:00
8	0:04:00	0:04:00	0:03:00	0:05:00	0:04:00	0:04:00	0:03:00	0:05:00	0:03:00	0:04:00	0:03:00	0:01:00	0:04:00	0:03:00	0:05:00	0:03:00	0:23:00
9	0:04:00	0:05:00	0:05:00	0:05:00	0:04:00	0:03:00	0:04:00	0:04:00	0:04:00	0:03:00	0:01:00	0:04:00	0:03:00	0:01:00	0:02:00	0:02:00	0:20:00
10	0:04:00	0:05:00	0:05:00	0:05:00	0:04:00	0:03:00	0:04:00	0:04:00	0:04:00	0:03:00	0:01:00	0:04:00	0:03:00	0:01:00	0:02:00	0:02:00	0:20:00
11	0:04:00	0:04:00	0:03:00	0:05:00	0:04:00	0:04:00	0:03:00	0:05:00	0:03:00	0:04:00	0:03:00	0:01:00	0:04:00	0:03:00	0:05:00	0:03:00	0:21:00
12	0:00:00	0:05:00	0:06:00	0:03:00	0:04:00	0:04:00	0:03:00	0:05:00	0:03:00	0:04:00	0:03:00	0:01:00	0:02:00	0:02:00	0:05:00	0:07:00	0:20:00
13	0:05:00	0:00:00	0:06:00	0:07:00	0:08:00	0:10:00	0:08:00	0:10:00	0:09:00	0:05:00	0:06:00	0:02:00	0:02:00	0:03:00	0:05:00	0:03:00	0:20:00
14	0:06:00	0:06:00	0:00:00	0:05:00	0:04:00	0:04:00	0:03:00	0:05:00	0:03:00	0:04:00	0:03:00	0:01:00	0:04:00	0:03:00	0:05:00	0:03:00	0:23:00
15	0:03:00	0:07:00	0:05:00	0:00:00	0:04:00	0:04:00	0:03:00	0:05:00	0:03:00	0:04:00	0:03:00	0:01:00	0:04:00	0:03:00	0:05:00	0:03:00	0:23:00
16	0:04:00	0:08:00	0:04:00	0:04:00	0:00:00	0:04:00	0:03:00	0:05:00	0:03:00	0:04:00	0:03:00	0:01:00	0:02:00	0:02:00	0:05:00	0:07:00	0:20:00
17	0:04:00	0:10:00	0:04:00	0:04:00	0:04:00	0:00:00	0:03:00	0:05:00	0:03:00	0:04:00	0:03:00	0:01:00	0:04:00	0:03:00	0:05:00	0:03:00	0:23:00
18	0:03:00	0:08:00	0:03:00	0:03:00	0:03:00	0:03:00	0:00:00	0:02:00	0:02:00	0:03:00	0:04:00	0:02:00	0:03:00	0:05:00	0:07:00	0:08:00	0:20:00
19	0:05:00	0:10:00	0:05:00	0:05:00	0:05:00	0:05:00	0:02:00	0:00:00	0:04:00	0:03:00	0:04:00	0:03:00	0:05:00	0:07:00	0:09:00	0:05:00	0:23:00
20	0:03:00	0:09:00	0:03:00	0:03:00	0:03:00	0:03:00	0:02:00	0:04:00	0:00:00	0:03:00	0:04:00	0:02:00	0:01:00	0:06:00	0:04:00	0:08:00	0:23:00
21	0:04:00	0:05:00	0:04:00	0:04:00	0:04:00	0:04:00	0:03:00	0:03:00	0:03:00	0:00:00	0:03:00	0:02:00	0:04:00	0:06:00	0:08:00	0:05:00	0:20:00
22	0:03:00	0:06:00	0:03:00	0:03:00	0:03:00	0:03:00	0:04:00	0:04:00	0:04:00	0:03:00	0:00:00	0:02:00	0:03:00	0:05:00	0:08:00	0:04:00	0:20:00
23	0:01:00	0:02:00	0:01:00	0:01:00	0:01:00	0:01:00	0:02:00	0:03:00	0:02:00	0:02:00	0:02:00	0:00:00	0:02:00	0:03:00	0:05:00	0:07:00	0:23:00
24	0:02:00	0:02:00	0:04:00	0:04:00	0:02:00	0:04:00	0:03:00	0:05:00	0:01:00	0:04:00	0:03:00	0:02:00	0:00:00	0:04:00	0:04:00	0:08:00	0:20:00
25	0:02:00	0:03:00	0:03:00	0:03:00	0:02:00	0:03:00	0:05:00	0:07:00	0:06:00	0:06:00	0:05:00	0:03:00	0:04:00	0:00:00	0:05:00	0:03:00	0:23:00
26	0:05:00	0:05:00	0:05:00	0:05:00	0:05:00	0:05:00	0:07:00	0:09:00	0:04:00	0:08:00	0:08:00	0:05:00	0:04:00	0:05:00	0:00:00	0:10:00	0:23:00
WP1	0:07:00	0:03:00	0:03:00	0:03:00	0:07:00	0:03:00	0:08:00	0:05:00	0:08:00	0:05:00	0:04:00	0:07:00	0:08:00	0:03:00	0:10:00	0:00:00	0:20:00
DS2	0:20:00	0:20:00	0:23:00	0:23:00	0:20:00	0:23:00	0:20:00	0:23:00	0:23:00	0:20:00	0:20:00	0:23:00	0:20:00	0:23:00	0:23:00	0:20:00	0:00:00