Challenges and Opportunities of Waste Management in IoT-enabled Smart Cities: A Survey

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Challenges and Opportunities of Waste Management in IoT-enabled Smart Cities: A Survey

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Abstract –The new era of Web and Internet of Things (IoT) paradigm is being enabled by the proliferation of various devices like RFIDs, sensors, and actuators. mart devices (devices having significant computational capabilities, transforming them to 'smart things') are embedded in the environment to monitor and collect ambient information. In a city, this leads to Smart City frameworks. Intelligent services could be offered on top of such information related to any aspect of humans' activities. A typical example of services offered in the framework of Smart Cities is IoT-enabled waste management. Waste management involves not only the collection of the waste in the field but also the transport and disposal to the appropriate locations. In this paper, we present a comprehensive and thorough survey of ICT-enabled waste management models. Specifically, we focus on the adoption of smart devices as a key enabling technology in contemporary waste management. We report on the strengths and weaknesses of various models to reveal their characteristics. This survey sets up the basis for delivering new models in the domain as it reveals the needs for defining novel frameworks for waste management.

Index Terms – Internet of Things; Smart Cities; Waste Management

1 INTRODUCTION

BY 2050, the vast amount of earth population (i.e., 70%) will move to urban areas, thus, forming vast cities [1]. Such cities require a smart sustainable infrastructure to manage citizens' needs and offer fundamental and more advanced services [2]. The adoption of Future Internet technologies enhanced by the use of the Internet Protocol (IP) on numerous wireless sensors enables the Internet of Things (IoT) paradigm. Numerous sensors have the opportunity to be part of Wireless Sensor Networks (WSNs). When WSNs are applied in a city, they are responsible for collecting and processing ambient information and, thus, to upgrade legacy city infrastructure to the so-called Smart Cities (SCs). A definition of the concept of SC is provided in [6]: "A Smart City is a city well performing in a forward-looking way in the following fundamental components (i.e., Smart Economy, Smart Mobility, Smart Environment, Smart People, Smart Living, and Smart Governance), built on the 'smart' combination of endowments and activities of self-decisive, independent and aware citizens". This definition incorporates the fundamental component of a smart environment which is mainly adopted for systems dealing with environmental pollution. The concept of smart environments depicts the ambient intelligence found in a SC through the adoption of smart devices and wireless networks. This way, intelligent applications could be delivered on top of such infrastructures. WSNs are capable of reforming activities in a SC in every aspect of daily life [3]. In this paper, we focus on a specific application domain, waste management. The efficient management of waste has a significant impact on the quality of life of citizens. The reason is that waste disposal has a clear connection with negative impacts in the environment and thus on citizens' health.

In this paper, we take advantage of our study of the waste management problem in the city of St. Petersburg, Russia. St. Petersburg is a city of 5 million citizens covering a total area of 1,439 square kilometers, a density of 3,391 citizens per square kilometer. On average, solid waste produced in the city is 1.7 million tonnes per year. The daily amount of municipal solid waste generated is 0.93 kilograms per citizen. On a daily basis, the municipality of St. Petersburg uses 476 waste collection trucks with a capacity of 5 tons per truck. The fuel consumed in one year is, on average, 1.8 million liters. The average costs spent for fuel in one year for waste collection is more than 1 million US dollars. Finally, the traffic congestion caused by the fleet of waste collection trucks at rush hours is significant due to the narrow roads and small backyards, causing indirect problems in citizens' activities. Obviously, it is critical to efficiently manage the waste disposed in every location of a SC not only focusing on the collection activities but also on its transport and recycling.

We model the waste management as a set of services on top of an IoT infrastructure in a SC. These services cover the following parts of a waste management scheme: (i) waste collection planning and implementation (e.g., routing solutions for collection trucks, dynamic adaptation of routes); (ii) transport of waste to specific locations (e.g., routing according to the type of waste); (iii) recycling and preparation for re-use. In this paper, we focus on the first type of services i.e., efficient planning of waste collection activities. We also focus on dynamic models on contemporary waste collection with the proliferation of Radio Frequency Identification (RFID), sensors and actuators [4]. Several devices have been adopted for enabling the efficient implementation of the dynamic waste collection e.g., RFID tags, sensors and

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actuators. With the term dynamic, we denote the ability of a system to change, in real time, the parameters and the plans that affect the collection of waste during the collection activity. Such functionalities could be incorporated into an intelligent transportation framework that results in real time directions provided to the collection trucks. Intelligent transportation contributes to dynamic waste collection since it uses smart vehicle infrastructure, which is incorporated in this survey [5].

Specifically, we present a comprehensive survey on the adoption of Information and Communication Technologies (ICT) in waste management models focusing on the modern ICT tools and technologies. We survey a substantial body of knowledge, thirty-two case studies. Among them, only six models involve an IoT-enabled technology. We argue that waste management solutions should be adopted as the back-end middleware to support further inference and reasoning on top of the data coming from sensors. We also discuss a taxonomy of the studied models and, thus, we are able to compare the strengths and weaknesses of each one.

The rest of the paper is structured as follows. Section 2 discusses the intelligent waste management and proposes a taxonomy adopted to compare waste management models. Section 3 reports on the survey of relevant models and the comparative assessment. Section 4 concludes the paper and discusses future work.

2. Intelligent Waste Management

2.1. The WSN/IoT Oriented Approach

A SC could incorporate various models to enable new services or efficient redesign of the existing services [8]. For instance, in the waste collection process, static models could be transformed to Waste Collection as a Service (WCaaS) which enables online dynamic scheduling and routing of the collection trucks [9]. Fig. 1 presents an example for both a static and a dynamic routing scenario for waste collection. The dynamic waste collection could be described as an online decision process for defining: (i) when to collect waste from bins (i.e., scheduling), and (ii) which routes the collection trucks should follow (i.e., routing). Many technologies and hardware are already used in waste management adopting different approaches in the management of the physical infrastructure as well as the data collected in the field. For instance, the IoT hardware and technology could identify real objects and transforms them to 'smart things' [10]. RFID can be used for tagging an object, and so gives a unique identifier to each smart thing [11]. Sensors and WSNs enable the measurement of physical quantities and the transformation to digital signals, which are processed wirelessly by an ad-hoc network infrastructure [12]. Low-power radio communications and low-cost embedded devices enable sensors to incorporate RFID tags [13]. Actuators are adopted to stimulate and give feedback to digital systems by interacting, in the physical layer, with the infrastructure [14]. Future Internet provides interconnection to smart things with IPv6 over Low Power Wireless Personal Area Networks (6LoWPAN) protocol, which is a modified version of IPv6 for low-power embedded devices [15]. In addition, many IoT architectures are built on Cloud Infrastructure (i.e., OpenIoT) [16], enabling the concept of Infrastructure as a Service (IaaS) [17]. Furthermore, the interconnected smart phones [18], form networks which serve as WSN gateways for IoT systems [19]. For instance, in the waste collection example, collection truck drivers can use a smart phone network enabling messaging with the waste management infrastructure and thus realize dynamic scheduling and routing [20]. Finally, the WSN/IoT's strength is that it can combine diverse technologies to support dynamic models for the efficient waste management in SCs.

In this paper, we review a high number of models in the waste management domain to reveal their pros and cons. The aim is to setup the basis for delivering novel models that will outperform the existing ones. However, before we are ready to propose and discuss any novel reference model for waste management, it is essential to compare the research related to the adoption of dynamic models for waste collection. For realizing a comparative assessment, we proceed with the definition of a concrete taxonomy that 'covers' the available models. The provided taxonomy will become the basis for mapping any waste management model, thus, to be compared with any other model found in the respective literature. Through the proposed taxonomy, the interested readers/researchers will be capable of identifying any 'gaps' in the respective research and propose efficient methods for dealing with new frameworks in the domain.

2.2. The Proposed Taxonomy

The current survey focuses on research approaches that incorporate modern ICT techniques and tools in SCs. The adoption of ICT technologies is depicted in our taxonomy. We report on the proposed taxonomy before we survey the existing research efforts to give the readers the necessary overview of the domain. Hence, the interested readers will be capable of easily identify the main characteristics of each model and their place in the respective literature.

We define the concept of waste management context that aims to setup the basis for classifying waste management models. The waste management context incorporates the hardware, tools, data and software that a waste management model adopts to become the basis for realizing a waste management solution. In general, the waste management context could be categorized in three main categories: (i) the physical infrastructure, (ii) the IoT Technology, and (iii) the software analytics. These categories are discrete which means that the relevant context of each model belongs only to one of the aforementioned categories. Our taxonomy is organized concretely (i.e., we pay attention not only to the infrastructure but also to the data and the required software) to cover a range of diverse components and features. Each contextual component and feature is assigned specific values denoting its rational existence in the proposed taxonomy. Components are related to the tools / hardware adopted in each category while features are related to the contextual information (e.g., data) adopted in each category / model.

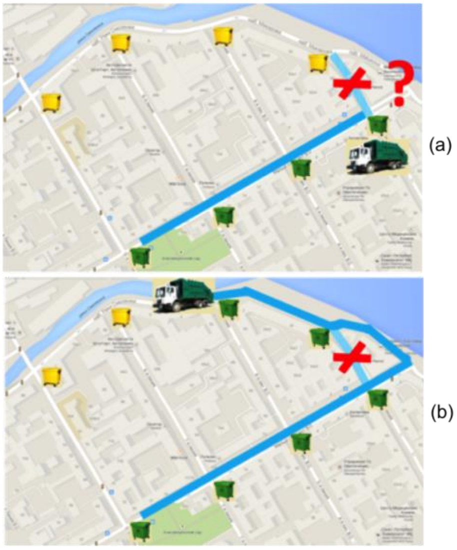

Fig. 1. (a) Static routing vs. (b) Dynamic routing. Dynamic routing adapts to real time emergency situations while static routing fails. Note: Green bins have already been collected while yellow ones are going to be collected.

The physical infrastructure involves the following components: (i) waste bins, (ii) pneumatic pipes, (iii) the fleet of trucks, (iv) depots, (v) dumps; and the following features: (i) bins location, (ii) recycling of inorganic waste and (iii) processing of organic waste. Bins can be further categorized according to the type of waste that they stock to: (i) organic, (ii) glass, (iii) paper, (iv) plastic, (v) metal, and (vi) toxic. The location of each bin differs according to their presence outdoors or underground. The fleet of the available trucks is characterized as homogeneous or heterogeneous according to the capacity the trucks can store. For instance, when the fleet of trucks has similar the same capacity, it is characterized as a homogenous fleet. On the contrary, when the fleet of trucks has different technical characteristics with variable capacity, it is characterized as a heterogeneous fleet. Depots are intermediate waste storage areas within the city. In our view, depots are important to serve as intermediate points in the waste collection process that will facilitate efficient waste management e.g., recycling. In the literature, recycling is widely studied as the efficient 'connection' of the collection process with the disposal at the recycling centers will maximize the positive effects of recycling in the economy and the society. Recycling centers or dumps, where waste is finally disposed, are usually located outside of the city and their number is related to the population. Waste collection can incorporate either a single or multiple depots.

The second category of the waste management context, i.e., the IoT Technology, focuses on the devices adopted to record and transfer ambient information, like: (i) RFID tags, (ii) Near Field Communications (NFC); (iii) sensors, (iii) WSNs (adopted for 'large-scale' communications), (iv) actuators, (v) cameras, and (vi) GPS. RFID tags are used for bin tagging and identification. Sensors are the fundamental component of IoT-enabled waste management and they are incorporated in the vast majority of the research efforts. They are specialized to measure a set of physical quantities like: (i) capacity, (ii) weight, (iii) temperature, (iv) humidity, (v) chemical reactions, and (vi) pressure. NFC and WSNs are adopted for transferring the data in the infrastructure. They are applied on top of sensors that interact wirelessly either with each other or with the backbone network infrastructure. Actuators are used by the system to interact with the waste bins, e.g., an actuator can lock the bin's lid when the bin gets full. Cameras can be treated as a special sensor for measuring the volume of a bin. Since cameras do not constitute an ordinary sensor but are part of a sensing utility they are examined separately. The last component IoT Technology is GPS; in contrast to the other equipment, it is incorporated on the collection trucks and not on bins. GPS is essential for location tracking during dynamic routing.

The last category of waste management context, i.e., software analytics, focuses on the following components: (i) the Decision Support System (DSS), which depicts the inference process to the stakeholders; (ii) the GIS, which focuses on the processing of the spatiotemporal context as a decision process criterion; (iii) the dynamic scheduling, which is responsible for deriving the exact time where the routing process will be initiated; (iv) the dynamic routing, which involves real-time changes in the pre-defined route to better serve the needs of on-going waste management to any change in the context. The algorithms adopted in the software analytics part of the contextual aspect of waste management are strictly dynamic which means that the proposed waste collection systems are comprised of pure ICT functionality. This means that a set of intelligent algorithms are proposed to facilitate the whole process from the collection to the final disposal taking into consideration various types of information to increase the performance. In addition, the software analytics part involves the following features: (i) the architecture, (ii) the social context and (iii) the experimental data. The architecture of a waste management system is either defined explicitly or implied as a part of the overall system design. The social context best describes the dynamics and social impacts of waste management on citizens. The last feature of software analytics is the experimental data used for evaluation of the proposed approaches. Data incorporated are either synthetic, created in the laboratories, or real, collected from observations in the SCs.

Table 1 presents an overview of the above discussed components / features while Fig. 2 visualizes the proposed taxonomy.

TABLE 1
TAXONOMY OF WASTE MANAGEMENT

Categories	Components / Hardware	Features
Physical Infrastructure	Bins Fleet of Trucks Depots Dumps Pneumatic Pipes	Recycling of Inorganic Waste Processing of Organic Waste Bins Location Bins Type
IoT Technology	RFIDs Near Field Communication (NFC) Sensors Wireless Sensor Networks Actuators Cameras GPS	
Software Analytics	DSS GIS Dynamic Scheduling Dynamic Routing	Architecture Social Context Experimental Data

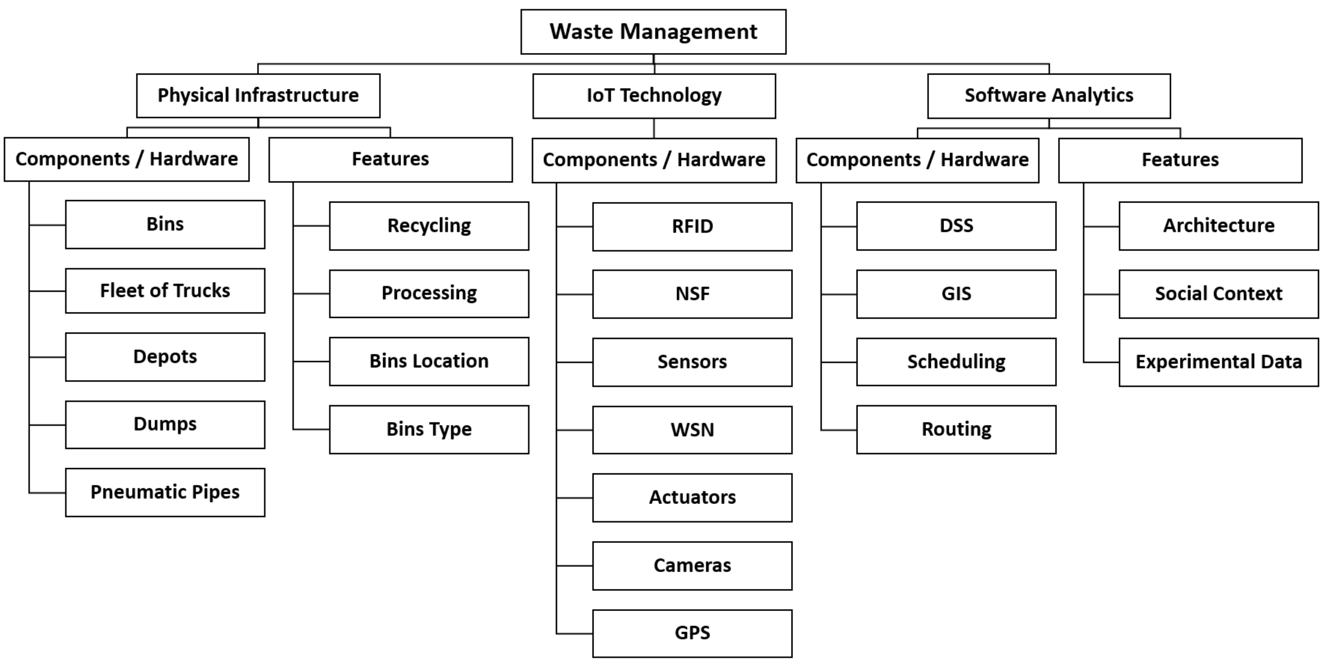

Fig. 2. Visual tree representation of the proposed taxonomy.

3. SURVEY AND COMPARATIVE ASSESSMENT

The efforts we review are compared according to the above proposed taxonomy while their strengths and weaknesses are clearly stated. These research efforts cover more than ten years of research in the area of ICT waste management. We survey thirty-two papers while only six exploit the IoT Technology as the back-end system for delivering intelligent applications. The distribution of the papers by the publication year is depicted in Fig. 3. Taking advantage of this survey, we propose a reference model which exploits IoT capabilities combining the strengths and eliminating the weaknesses of the surveyed models.

3.1. Survey of Existing Models

In [21], the authors propose a capacitive level-sensing model for solid waste collection. The paper presents a capacitive point-level sensor used for improved solid waste collection. the sensor is composed of two electrodes built from low-cost metal tape which has the ability to detect the volume of paper waste in the bin. The research uses a theoretical model which describes qualitatively the effects of the presence of closely related conductive outdoors or underground metallic objects. Face-to-face electrodes are proved to be less sensitive to interference from close metallic objects and the position of paper in the bin. Furthermore, the paper defines a capacitance threshold that can be applied to a certain type of bin, thus, it can depict when the bin is full. Compared with our taxonomy, in the physical infrastructure, paper waste bin is the appropriate class. They are located either outdoors or underground. The fleet of collection trucks is homogenous and a single dump is used. Recycling of inorganic waste is also supported. Moreover, regarding the IoT Technology, in the presented system, a capacity sensor for solid waste collection is used. The software analytics part involves evaluation with synthetic experimental data. In general, the strengths of the system involve the well-defined analyses and design of the capacity sensor. However, the system does not constitute a concrete approach as it focuses strictly on the technical characteristics of a specific type of sensor.

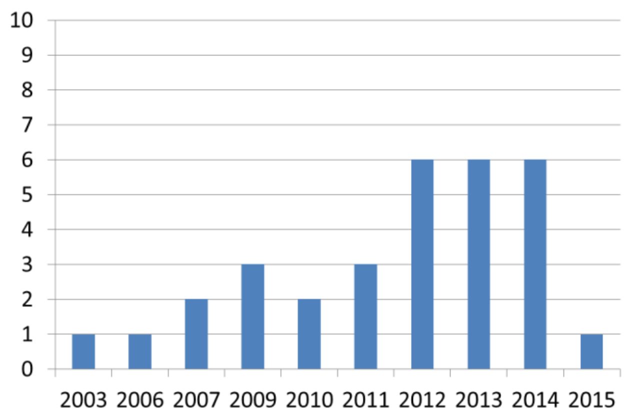

Fig. 3. Distribution of the papers by the publication year. Note: x-axis unit of measure is the research's publication year while y-axis unit of measure is the number of research publications for a specific year.

A search space analysis for dynamic routing with time windows in waste collection is discussed in [22]. The paper presents a large-scale, dynamic routing model with time windows taking into consideration multiple disposal trips and drivers' lunch breaks. A fitness search space analysis for a variety of waste collection scenarios is described by utilizing statistical and information theoretic parameters. The authors conclude that using such parameters, the mutation landscapes are more easily distinguishable than crossover landscapes. Comparing with our taxonomy, the physical infrastructure involves outdoor, organic waste bins. The fleet of the collection trucks is homogenous and depots are incorporated while a single dump is used. Moreover, the IoT Technology involves capacity sensors and the software analytics include an overview of the dynamic routing. The model is evaluated with synthetic data. The strengths of the paper are the incorporation of drivers' lunch breaks as a routing parameter along with the multiple disposal trips. However, the paper does not define a concrete architecture.

In [23], the authors propose a Web-based Decision Support System (DSS) for waste lube oils collection and recycling. The DSS enables schedulers to perform interactive reverse supply chain management operations. The main goal is related to the efficient and effective management of waste lube oils collection and recycling. A model which enables intra-city and inter-city dynamic routing incorporating real-time operational constraints is proposed. Dynamic routing is based on the shortest path and hybrid metaheuristics models. The paper introduces an Enterprise Resource Planning (ERP) system which enables the utilization of specific functional models and the combination with other scheduling tools. The proposed DSS provides online monitoring of the waste collection process and the Web architecture enables the platform independent approach for exploiting wireless telecommunication utilities. Finally, the proposed system is applied to realistic industrial environments and is proved to increase productivity and competitiveness on reverse supply chain management. Compared with our taxonomy, the physical infrastructure involves outdoor toxic waste bins and the fleet of the collection trucks is heterogeneous. Recycling of inorganic waste is supported. Moreover, the IoT Technology includes capacity and chemical sensors while WSNs are adopted as part of the proposed architecture. Collection trucks have embedded GPS devices for tracking their location and being synchronized with the central system. The specific research incorporates both a DSS and a GIS component in the software analytics part. The model is evaluated with real experimental data associated with WSNs traffic and the collection trucks. The strengths of the paper are the envisioned dynamic scheduling model along with the dynamic routing. However, the paper describes only the specific type of toxic lube oil waste bin.

In [24], the authors propose a model for remote monitoring of charity assets to improve the efficiency of the waste collection. The paper presents the waste collection problem from the collection costs perspective of servicing a major UK charity's: (i) donation banks and (ii) collection of unsold goods from retail shops. The research also states that currently bank and shop waste collection is based on static scheduling on fixed days of the week irrespective of the amounts of waste to be collected. A model from a major UK charity is proposed to monitor bank and shop servicing requirements. The system incorporates sensors embedded into bins and uses tabu search methods; to develop dynamic scheduling and routing models. The dynamic models are proved to decrease collection costs compared with the existing fixed scheduling infrastructure by means of distance covered, pollution emitted and the transported waste capacity. The physical infrastructure includes organic, glass, paper, plastic and metal waste bins located outdoors. The fleet of trucks is heterogeneous while a single dump is used. Recycling of inorganic waste and further processing of organic waste are supported. The IoT Technology includes WSNs while the software analytics part involves dynamic scheduling and routing. Finally, the model is evaluated with real experimental data collected from trucks in a period of a year. The strengths of the paper are the treatment of waste collection problem from the collection cost perspective along with the incorporation of tabu search methods. However, the paper neither defines a concrete architecture nor incorporates a DSS.

3.1.1 Models that adopt Capacity, Weight, Temperature, Humidity and Chemical Sensors

In [25], [26], [27], and [28], researchers adopt capacity, weight, temperature, humidity and chemical sensors for solid waste collection. Specifically, in [25], the authors propose a municipal solid waste platform exploiting recycling collection information based on IoT Technology. The paper presents a model for waste collection, transportation, recycling and processing. A management information platform based on IoT Technology is proposed which serves a waste collection model in the city of Wuhan. The outcomes of the research help municipal authorities to use efficiently the information produced in every stage of the waste collection process and, finally, achieve the goal of an intelligent cycle. In [26], the authors propose a dynamic optimization model for solid waste recycling. The paper presents a model for recycling materials and dynamic optimization. A dynamic decision model characterized by state variables is developed; it corresponds to the quality of waste in each bin on a daily basis. The model controls the variables, thus determining the quantity of the collected materials. It is also responsible for calculating the routes for each collection truck. An objective function is defined that is studied to minimize the sum of the collection costs. The decision model is integrated in a DSS that is enabled with a GIS. A case study in the municipality of Cogoleto, Italy is presented which proves the effectiveness of the proposed model. Specifically, the net benefits of the optimized waste collection are 2.5 times greater than the estimated current policy. In [27], the authors propose a solid waste bin and truck monitoring system enabled with RFID and ICT. The paper presents an integrated system for the efficient waste collection. GPS, GIS and cameras are adopted to design an intelligent monitoring system for bins and trucks. A novel integrated theoretical framework, a hardware architecture and an inference algorithm have been introduced, as well. The model incorporates a database which stores bin and truck information. In addition, it processes the date and time of waste collection, the bin status, the amount of waste transported and trucks GPS coordinates. Data are exploited by the proposed monitoring system in order to perform efficient scheduling and routing. The monitoring system uses an advanced GUI which incorporates real time image processing, histogram analysis, waste estimation, and bin information. Experimental results prove that the proposed monitoring system is stable and has high performance. A WSN prototype for solid waste bin monitoring with an energy efficient sensing model is proposed in [28]. The research extends [27] by describing a system that responds online when waste is disposed in the bins. The paper presents a system architecture which is composed by three tiers. The lowest tier involves the sensors embedded in the bins while an energy efficient model senses the measurements and transmits bin status to the next tier. The middle tier includes a gateway which stores and transmits bin data to a control station. The upper tier stores and analyzes the data for further use. The system is capable of minimizing the truck operational costs and pollution emissions by providing the collected data to a DSS which incorporates dynamic routing for waste collection.

Organic, paper, plastic, metal and toxic waste bins located outdoors are involved in [25], [28] while glass, paper, plastic and metal waste bins are involved in [26], [27]. In all efforts, the bins are located outdoors. The fleet of the collection trucks is homogenous in [25], [27], [28] and heterogeneous in [26]. Recycling is supported in all the efforts and the IoT Technology involves RFID tags [25], [27], [28], cameras [27], GPS [26], [28], while WSNs is the main communication hub for all. GPS is embedded on trucks enabling the collection of real time information, thus, enhancing the dynamic routing of trucks in real time. Real experiment data are adopted in [25], [26], [27] while both real and synthetic data are adopted in [28]. Concerning the strengths of the discussed models these are as follows. In general, many advantages in the proposed frameworks offer the efficient management information platform and the extensive use of the IoT Technology [25], specific objective functions that minimize the cost of waste collection [26], intelligent monitoring systems for bins and trucks [27], or the adopted DSSs [28]. The adopted DSSs aim to respond online when waste is disposed and minimize the truck operational costs and pollution emissions. On the other hand, one can observe a set of disadvantages. Among them the most critical are the absence of a DSS for deriving decisions in real time [25], the absence of IoT hardware (e.g., RFIDs) [26] and actuators [28] or the involvement of a single type of sensor [27].

3.1.2 Models that adopt Capacity, Weight, Temperature, Humidity and Pressure Sensors

The researchers in [29] and [30] focus on the use of capacity, weight, temperature, humidity and pressure sensors for solid waste collection. More specifically, in [29] the authors have proposed a sensorized waste collection container for content estimation and collection optimization. The paper presents the design and implementation of a suitable urban solid waste system which can predict the quantity and diversity of solid waste. They adopt measures to correlate the capacity of solid waste with residential population and consumer index at different seasons of the year. The system incorporates an intelligent and sensorized bin in order to exploit data used for further statistical inference processes. The proposed bin is prepared and tested in the Pudong New Area, Shanghai. In [30], the authors have proposed a solid waste collection architecture using WSNs. The paper presents a WSN model as a key enabling technology for smart implementation to face the waste collection problem in an urban area. An architecture is proposed in order to improve and optimize the on-site handling and transportation during the waste collection process. The system architecture incorporates sensor nodes and uses data transfer nodes in order to provide data measurements, collected from bins, to a remote server. A remote monitoring web application is also incorporated, providing user the capability of interacting with the system through a Web browser. A DSS is also available aiming to provide solutions to resources organization problems.

Compared with our taxonomy, physical infrastructure involves outdoor organic, glass, paper and plastic waste bins in [29] while in [30] only organic, glass and paper waste bins are included located outdoors. Regarding the IoT Technology, cameras are incorporated in [29], WSNs in both i.e., [29] and [30] and GPS in [30]. Regarding the software analytics, the model discussed in [29] is evaluated on top of real experimental data collected from sensors located on bins in the city of Pudong while the model presented in [30] is evaluated by synthetic data. In both efforts, the fleet of trucks is homogenous. The strengths of the model presented in [29] are the enhancement of the bins with a variety of sensors and the use of cameras. However, the paper does not support a WSN for further fusion of the sensor data neither supports RFID for bin tagging and identification. The strengths of the model discussed in [30] are the use of WSN as the back-end communication component, the detailed presentation of the underlying architecture and the incorporated remote monitoring GUI. However, the paper does not incorporate actuators as an integration mechanism of the model.

3.1.3 Models that adopt Capacity and Weight Sensors

The next set of papers in the area consist of five research efforts where the authors also deal with capacity and weight sensors [31], [32], [33], [34], [35]. More specifically, in [31] the authors propose a collection-monitoring model for early detection and evaluation of waste through sensorized bins. The research extends [29] by describing a novel application used to monitor the municipal solid waste, based on distributed sensor technology and GIS. The paper presents a model tested and evaluated in Pudong, Shanghai (PR China). The waste collection system has specific monitoring requirements related to the rapidly increasing rate of waste production. The paper focuses on the quantitative measurement of the waste present at each bin and identification of different types of waste collected in the bins. The model incorporates a network of sensorized bins linked to a DSS. Bins are equipped with a set of sensors which provide real data to the system while trucks incorporate GPS for real time monitoring. The collected data are integrated into an existing application used by municipality authorities. Evaluation is performed on real data flow (the software analytics part) from the network of bins as well as in terms of optimization functions such as dynamic scheduling and routing. Research uses obtained outcomes related with waste weight and volume as parameters for optimizing the proposed dynamic routing model and evaluating the material density in the bins. In [32], the authors have proposed an energy utilization model for optimizing solid waste collection, which is applied in a large city area. The research extends [31] by providing three models for dynamic scheduling and routing enhanced with path optimization. The paper presents an improved waste collection model which is enabled with capacity and weight data collected for bins. In addition, it is exploited energy utilization related to the trucks, which optimize municipal solid waste processes. A genetic algorithm and a simulation model are adopted to optimize the collection route. There are incorporated in both a DSS and a GIS for efficient administrative management of the system. The proposed model is verified through a case study in Pudong. The results are very promising for waste collection and transport by achieving energy utilization. In [33], the authors have proposed a model for analyzing the impact of solid waste Source Segregation (SS) intensity on fuel consumption along with the collection costs. The paper presents an evaluation on the fuel consumed and an analysis on the collection costs of solid waste collection. A simulation model is incorporated as well. The proposed model can calculate the time spent, the waste capacity collected and the fuel consumed for a specific waste collection route. The initial value of SS intensity is set to 25% where the evaluated model error was less than 1.2. The simulation scenarios are held with different values of 25%, 30%, 35%, and 52% of SS intensity. An increase in the average fuel consumed by collection trucks is observed started form 3.3 lit/ton for 25% SS intensity and reached up to 3.8 lit/ton for SS intensity of 52%. In addition, direct collection costs; including crews and truck purchase, ranged from 40€/ton to 70€/ton, respectively, for 25% and 52% of the SS intensity. The research proves that the increased values of fuel consumed and collection costs depend on the density of the waste collected, on the collection truck compaction ratio and on the Waste Collection Truck Utilization Factor (WCTUF). Specifically, a particular reduction of 50% of the WCTUF can lead to an average increase of 80% in fuel consumed and 100% in collection costs. In [34], the authors propose a Web-GIS for optimizing the viability of MSW selective collection in developed and transient economies. The paper presents issues related to the implementation of the Web-GIS system. The model is critically evaluated with two scenarios: (i) two Europeancase studies, and (ii) two extra-European case studies. In the first scenario, one of the best examples of selective collection optimization in Italy is evaluated with Web-GIS systems. In this scenario, 80% efficiency of waste source separation in the recycling purposes is achieved. In the second scenario, the local authorities incorporate optimization of waste collection with Web-GIS technologies for the first time. The results in the second scenario indicate that it needs more effort to achieve optimized management of MSW. Specifically, the last two case studies are pilot experiments in China and Malaysia. The research performs comparative assessment comparing the Web-GIS strategies, between each case study for the developed and transient economies, respectively. It is concluded that transient economies are willing to exploit Web-GIS utilities for MSW collection. In [35], the authors propose a model for smart planning and monitoring of urban solid waste management using the Smart-M3 platform. The paper presents the process of solving the waste collection problem by incorporating context from interconnected heterogeneous devices and sharing data involving a large amount of urban population. A Smart-M3 platform, exploiting the IoT Technology, is proposed offering a high degree of decoupling and scalability. Sensors enable real time monitoring of the waste capacity. A DSS is responsible to integrate this information to perform dynamic routing within a certain territory. The paper defines advantages to both service providers and users. Specifically, service providers can obtain a significant cost reduction; while users gain high Quality of Service (QoS). Furthermore, the model is interactive since users can communicate with the system and be aware of the waste capacity stored in neighbor bins. Green points are also incorporated in order to enable recycling.

Compared with the proposed taxonomy, the effort presented in [31], [33], [34] involves organic, glass, paper, plastic and metal waste bins located outdoors (physical infrastructure). The fleet of trucks transporting the waste is homogenous in [31] and heterogeneous in [33], [34]. A single dump is used in [31], [33] and multiple in [34]. The IoT Technology uses RFIDs [34], WSNs [31], [33] while cameras are incorporated as part of the sensor infrastructure for [31], [33]. GPS is embedded on trucks enabling real time information transfer, thus, enhancing dynamic routing. Furthermore, regarding the software analytics the discussed architectures incorporate a DSS and a GIS. Finally, the model was evaluated on real experimental data collected from sensors located on bins in the city of Pudong [31] and a large section of a medium-sized Italian city, which consists of a typical cities centre, mainly with apartment buildings and with a rather high population density [33]. In [32], regarding the physical infrastructure includes organic, glass and toxic waste bins located outdoors, the fleet of trucks is homogenous and a single dump is adopted. Recycling of inorganic waste and further processing of organic waste are supported. Moreover, WSNs, a DSS and a GIS are discussed. Dynamic scheduling and routing are also defined. Finally, the model was evaluated on real experimental data collected from sensors located on bins also in the city of Pudong. The model presented in [35], adopts glass, paper, plastic, metal and toxic waste bins while the fleet of trucks is homogeneous. Multiple dumps are used. Recycling of inorganic waste is supported. GPS embedded on trucks is incorporated for location tracking while software analytics incorporates a DSS. Dynamic routing is defined and social context is supported. Finally, the model was evaluated on real experimental data from sensors and trucks. The effort in [31] extends [29] by incorporating a WSN. However, the model does not support RFIDs for bin tagging and identification. The strengths of [32] are the enhanced genetic algorithm and the provided simulation model. However, the model does not support RFIDs. The strengths of [33] are the detailed simulation model and the variety of scenarios used to evaluate it. However, no architecture or a contemporary DSS are defined. The strengths of [34] are the well-defined Web-GIS system along with the two evaluation scenarios while the model does not incorporate a DSS or a dynamic scheduling algorithm. The strengths of [35] are the scalable platform, which incorporates context from interconnected heterogeneous devices and sharing data along with the exploitation of the IoT Technology. On the other hand, the paper does not incorporate RFIDs, as a key mechanism of IoT or a dynamic scheduling model.

3.1.4 Models that adopt Capacity and Pressure Sensors

In [36] and [37], researchers adopt capacity and pressure sensors for solid waste collection. The authors in [36] propose an economic performance comparison between pneumatic and door-to-door waste collection systems in existing urban areas. The paper presents an analysis on how a hypothetical stationary pneumatic waste collection system can be compared economically to a traditional truck-operated door-to-door collection system. In densely populated urban areas both pneumatic and door-to-door waste collection systems face disadvantages. Specifically, buildings and fixed city infrastructure increase the installation costs of a pneumatic system in existing residential areas. Inversely, the limited space for waste transportation trucks and bins cause problems for truck-operated waste collection systems. The paper uses a method for analyzing the cost effects of the waste collection systems, which takes into consideration the monetized environmental effects of both waste collection systems. Door-to-door waste collection is proved to be economically six times more superior; approximately. In the performed analysis, the dominant cost factor is the large investment cost of the pneumatic system. Another significant impact factor is the economic value of land, because it is able to reverse the results of the analysis; in case that the value of land saved with pneumatic system is sufficiently high. In [37], the authors propose an automatic waste collection system based on Ubiquitous Sensor Network (USN). The paper presents a novel approach to collecting municipal solid waste in residential and commercial buildings using IoT Technology. USN technology eliminates web of wires while increases connectivity of devices, thus, providing an easy extension of the network. An USN architecture is proposed which is experimentally evaluated with real time scenarios in the city of Seoul, South Korea. The system is composed of integrated WSNs, gateways and specially designed software. The research covers all the processes of waste collection including waste loading and transportation in pneumatic pipes from depots to dumps. The proposed system is compared with a conventional wired network and proved to perform in-time fast waste collection. Furthermore, it has low installation, operational and maintenance costs; while it is scalable and reliable. Compared with our taxonomy, organic, glass, paper, plastic and metal waste bins are used which are located outdoors in both models (i.e., [36], [37]). Pneumatic pipes infrastructure is incorporated and the fleet of trucks is homogenous. Multiple dumps are used. Recycling of inorganic waste and further processing of organic waste are supported only in [36]. WSNs are implied in both efforts while dynamic scheduling and routing are defined with social context being supported. Finally, models were evaluated on real experimental data retrieved in the cities of Helsinki and Seoul. The strengths of the models are the detailed analysis of the hypothetical stationary pneumatic waste collection system, the comparison with a traditional truck-operated door-to-door collection system by means of economics efficiency, the well-defined USN architecture and the exploitation of IoT Technology.

3.1.5 Models that adopt RFIDs

In [38], [39], [40], [41], [42], and [43] the researchers incorporate extensively RFIDs for tagging and identification as part of the solid waste collection infrastructure. Specifically, in [38] the authors have proposed an RFID-based real time smart waste collection system. The paper presents the use of RFID and weight sensor technology as part of waste collection. The IoT architecture is proved to decrease waste collection operational costs and enables automating and streamlining waste identification for recycling and further processing of waste. Furthermore, weight measurement processes are incorporated in the proposed real time waste collection system. The paper concludes with an application that exploits RFID and weight sensor data in order to define an automatic Waste Identity, Weight, and Stolen Bins Identification System (WIWSBIS). In [39] the authors have proposed a waste collection multi-objective model based on real time traceability data. The paper presents the investment, operational and environmental costs related with the waste collection. A variety of IoT mechanisms is used in order to provide the system with real time data used to implement an efficient and innovative waste collection routing model. The research states that knowing the real-time data of each truck and the real replenishment level at each bin enables dynamic scheduling and routing in relation with a waste generation pattern. Dynamic models can be optimized incorporating further information about total distance covered, necessary number of trucks and the environmental impact. It is also described a framework about enabling traceability and monitoring in the optimization of solid waste collection. The framework is integrated with an innovative dynamic routing model which uses real time traceability data from an Italian city of 100,000 inhabitants. The model was tested and validated using simulation; while it is also performed an economic feasibility study. In [40] the authors have proposed an automated bin level detection system using a gray level aura matrix. The research extends [27] by introducing an advanced image processing approach integrated with communication technologies and a camera for bin level detection. The paper presents the environmental concerns associated with bins and the kind of waste disposed in them. A Gray Level Aura Matrix (GLAM) approach is used in order to extract the bin image texture. GLAM neighboring system parameters are tuned to determine their optimal values. The system is evaluated by training and testing the extracted image with Multi-Layer Perceptions (MLPs) and K-nearest neighbor (KNN) classifiers. The paper proves that the proposed system performance is robust and can be applied to different kinds of waste and bin level detection under various conditions. In [41] the authors have proposed a novel dynamic scheduling and routing model incorporating GIS, which reduce the operation costs and pollutant emissions of MSW collection. The paper presents an innovative methodology for the reduction of the operational costs and pollutant emissions involved in the waste collection and transportation. Dynamic scheduling and routing are combined for efficient waste collection. Dynamic routing is based on historical data initiated by the filling rate of each bin individually in order to establish the daily routes of collection points to be visited. This approach is more realistic compared with the usual assumption of a single average fill-up rate because it is common to all system bins. Dynamic routing enables ahead planning of the dynamic scheduling; which permits a better system management. The optimization process of the traversed routes incorporates a GIS and uses total spend time and covered distance as optimization criteria. The model also considers variables related to fuel consumption, pollutant emissions, truck speed and capacity transported as part of the optimization process. Experimental evaluation is performed for the case of glass waste collection and transportation in the city of Barreiro in Portugal. The research isolates the influence of the dynamic load; on fuel consumed and pollution emitted, by incorporating a sensitivity analysis of the truck loading process. Specifically, it was tested two scenarios of waste collection: (i) one with the collected waste capacity increasing exponentially along the collection path, and (ii) the other assuming that the collected waste capacity decreasing exponentially along the same path. Optimization performed on operation costs of labor, truck maintenance and fuel consumptions; as well as pollutant emissions, are proved to have beneficial impacts regardless of the optimization criterion used. Nonetheless, this impact is particularly relevant when optimizing for time; yielding substantial improvements to the existing system. In addition, it is proved that dynamic loading process of the collection trucks impacts on both fuel consumed and pollution emitted. In [42] the authors have proposed a solid waste disposal system using mobile ad-hoc networks. The paper presents a model for waste collection of bins, distributed in a highly densely populated city in India. A dynamic multi-hop network that can provide real time information to municipal authorities is formed. The system is able to monitor online and visualize the status of the bins for further use; due to sensors and adhoc transceivers embedded in the bins. In [43], the authors have proposed a model for assessing and improving management practices in planning packaging waste collection systems. The paper presents a packaging model for waste collection systems that incorporates depots as transfer and sorting stations. During the application of the current strategy each depot is managed independently and not as a part of the whole system. The research proposes four tactical and operational practices which contribute to the independent management of each depot. The model applies these practices to the proposed infrastructure and assesses their impacts on the total collection cost. A design methodology is developed to plan service areas, dynamic scheduling and routing. The model exploits alternative solutions in managing the system as a whole. The methodology is applied to real use cases of a waste collection and packaging company which serves 7 municipalities in mainland Portugal. The results were encouraging because of the decreased total cost of the system. The decrease in total cost was achieved because of the significant savings obtained in terms of minimizing: (i) the total distance covered, and (ii) the number of trucks required for waste collection.

Compared with our taxonomy, organic, paper, plastic and metal waste bins are adopted with a homogeneous fleet of trucks.

Recycling of inorganic waste and further processing of organic waste is supported. Weight sensors, capacity sensors GPS, cameras and RFIDs are used as part of the proposed architectures. Dynamic routing and dynamic scheduling are incorporated into the discussed systems while their evaluation is based on real experimental data. The strengths of the discussed efforts are the incorporation of RFIDs and the exploitation of the underlying architecture [38], the well-defined framework for enabling traceability and monitoring as well as the proposed dynamic scheduling and routing models [39], the advanced image processing [40], the incorporation of GIS and the advanced dynamic scheduling and routing models [41] and the incorporation of a dynamic multi-hop network along with the online monitoring and visualization utilities [42]. It should be noted that the application on real use cases of waste collection schemes helps in the efficient management of waste [43]. The observed limitations involve the orientation to a specific type of sensor [38], [39], [40], [41], [42], [43] and the absence of an architecture [40].

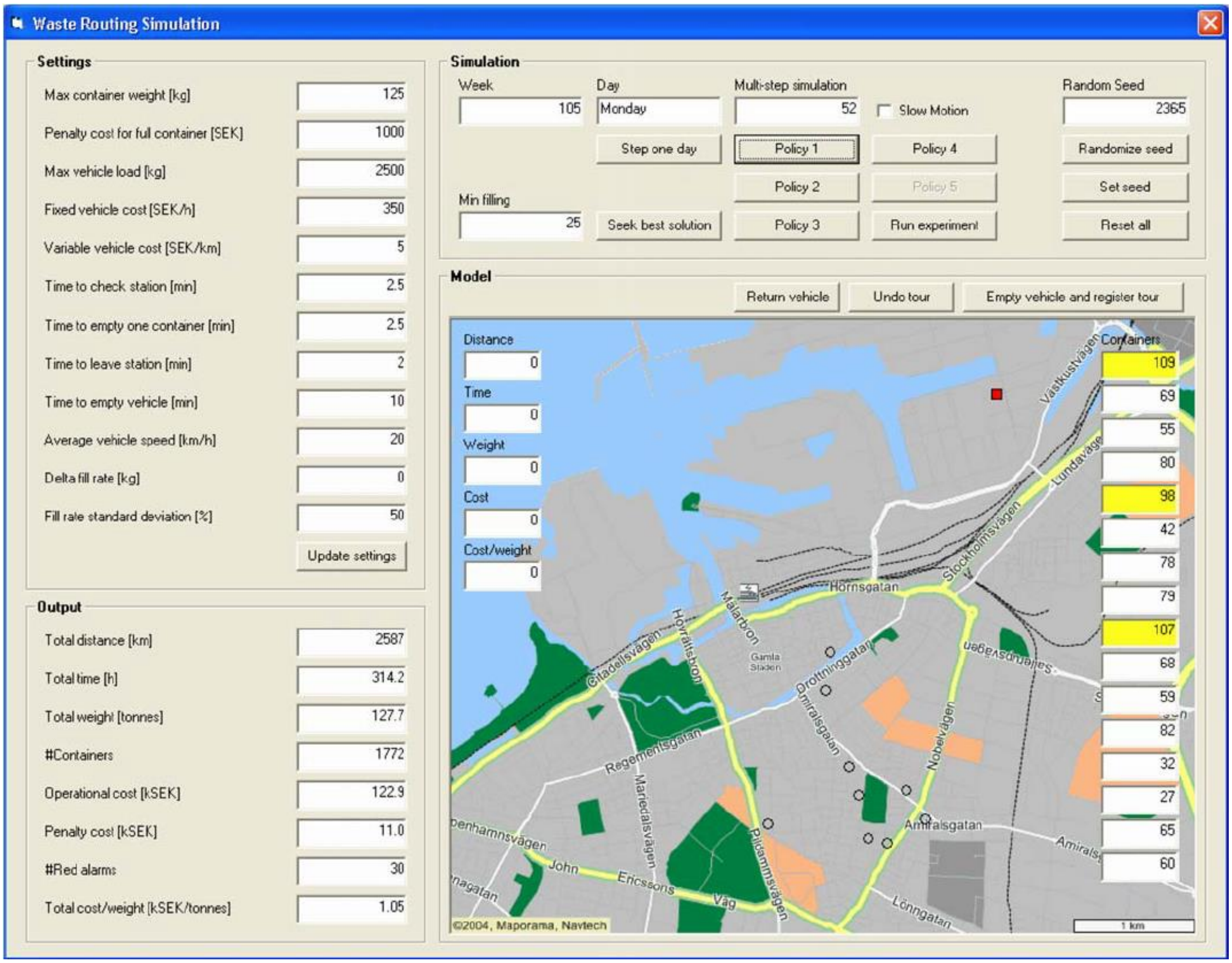

Fig. 4. The Malmoe simulation model in [44].

3.1.6 Models that adopt WSNs

The next set of papers, i.e., [44], [45], [46], [47], also focus on the extensive use of WSNs. More specifically, in [44], the authors propose a solid waste collection system, which incorporates an effective dynamic scheduling, and routing model. In Fig. 4, it is presented the Malmoe simulation model proposed in the paper. The paper presents capacity sensors and wireless communication equipment embedded to recycling bins. In the IoT infrastructure, the research effort provides waste collection operators and access to real time information about of the status of each bin. The architecture uses analytical modeling and discrete-event simulation to evaluate dynamic scheduling and routing by utilizing real-data. Furthermore, the discussed research performs an empirical simulation based on real experimental data from a recycling station in Malmoe, Sweden. During this study, it is proved that dynamic scheduling and routing models have lower operational costs, shorter collection and hauling distances, and reduced labor hours compared with static models. In [45], the authors have proposed an eco-design Machine-to-Machine (M2M) system that contributes to waste glass collection i.e., the Product Service System (PSS). The research methodology is based on the Life Cycle Analysis (LCA) model. The provided results help to understand the mechanisms of the PSS while research explains how the proposed infrastructure impacts the environment. The paper examines the influence of system parameters to eco-design and dimensioning of the PSS. The study incorporates mutualisation analytics to reduce environmental impacts while limiting data exchanges. Additionally, in [46], the authors propose a wireless platform, called WEKO, for monitoring the recycling spots. The paper presents an embedded WSN for monitoring the level of bins located in recycling spots. The system interacts with a remote central station when a bin reaches some filling threshold, thus, avoiding to check the spot if the bin is full while ensuring that the recycling spot is kept clean. The wireless nature of the system imposes energy supply requirements which are covered with specific batteries with a life time of at least six years. Data collected from sensors are captured by a monitoring platform located in the remote central station for further processing. In [47], the authors propose an inventory routing model for dynamic waste collection. The paper presents the process of waste collection incorporating underground bins equipped with sensors. The research treats the waste collection routing as a reverse inventory dynamic routing problem taking into consideration decisions involving routing and bin selection. The model is able to cope with uncertainty on the bins capacity and fluctuations of routes; due to daily and seasonal effects. The need of an anticipatory policy which will balance the workload over time is also stated. The paper proposes a computational efficient heuristic which consists of several tunable parameters depending on a weekly schedule. The parameters are tuned using optimal learning techniques as part of a simulation model. The research is applied and evaluated on a real use case problem of a waste collection company located in the Netherlands. The results show that the total cost savings are up to 40% due to the efficient optimization of parameters.

The strengths of the model presented in [44] are the enhancement of dynamic scheduling and routing models and the incorporated simulation model. However, the model is not integrated since it does not incorporate a DSS for processing the aggregated data. The strengths of the second model [45] are the incorporation of mutualisation analytics to reduce environmental impacts and the multi-criteria LCA used to feed the realistic scenarios. On the other hand, the paper describes only the specific type of glass waste bin. The advantages of the third model [46] are the contemporary embedded wireless sensor network and the system architecture, which handles energy supply requirements. The paper does not incorporate RFIDs as an assistive technology to the system architecture. In addition, only a specific type of capacity sensor is incorporated. The strengths of the fourth model [47] are the proposed inventory routing algorithm along with its application to the sensorized underground bins. However, the paper does not incorporate a DSS or a GIS.

3.1.7 Models that adopt Actuators

In [48], [49], [50], [51] and [52] the researchers incorporate actuators as part of the solid waste collection infrastructure. Specifically, in [48], the authors propose a bin level detection model based on a gray level co-occurrence matrix feature (GLCM) extraction approach. The research extends [40] by focusing on solid waste bin level detection and classification using the GLCM feature extraction. The paper also presents a set of GLCM displacement and quantization parameters along with the number of textural features which are tuned to determine the best parameter values of the bin images. Parameters and textural features are incorporated in the GLCM database adopted for reasoning. Image classification and grading is based on training and testing of MLPs and KNN classifiers. The proposed model can be used in bin level classification and grading, thus, providing a robust solution for bin detection, monitoring and management. In [49], the authors propose a solid waste bin detection and classification model using Dynamic Time Warping (DTW) and MLP classifiers. The research extends [48] by focusing on image processing solutions for solid waste collection. The paper presents the process of capturing bin image with a camera embedded in the bin. Specifically, during capturing the bin image the position of the camera should be focus on getting a centralized image of the bin area. The captured image should be further processed in order to correctly estimate the waste capacity in the bin. The research uses DTW for detecting and cropping the bin area; while Gabor Wavelet (GW) is incorporated for feature extraction of the bin image. The features extracted are then used to train a MLP classifier which is adopted to classify the bin level and perform estimations about the capacity of the waste in the bin. The classifier performance is evaluated with Receiver Operating Characteristic (ROC) curves and proved to be efficient with respect to the accuracy (i.e., level estimation of 98.5%). In [50], the authors propose an efficient waste collection model incorporating shortest path semi-static and dynamic routing. The paper presents the waste collection process from the IoT Technology perspective. It analyzes the importance of dynamic routing models as part of waste collection in SCs. The research introduces both a semi-static and a dynamic routing model as part of a two-tier architecture. Specifically, the upper tier contains a semi-static routing model which builds an initial route for waste collection. The lower tier contains a

TABLE 2
COMPARATIVE ASSESSMENT

	Physical Infrastructure								IoT Technology						Software Analytics						
Research Effort	**Bins Type**	**Bins Location**	**Pneumatic Pipes**	**Fleet of Trucks**	**Depots**	**Dumps**	**Recycling**	**Processing**	**RFIDs**	**Sensors**	**WSNs**	**Actuators**	**Cameras**	**GPS**	**Architecture**	**DSS**	**GIS**	**Dynamic Scheduling**	**Dynamic Routing**	**Social Context**	**Experimental Data**
[21]	3	1, 2	2	1	2	1	1	2	2	1	2	2	2	2	2	2	2	2	2	2	1
[22]	1	1	2	1	1	1	2	2	2	1	2	2	2	2	2	2	2	2	1	2	1
[23]	6	1	2	2	1	1	1	2	2	1, 5	1	2	2	1	1	1	1	1	1	2	2
[24]	1, 2, 3, 4, 5	1	2	2	2	1	1	1	2	1, 6	2	2	2	2	2	2	2	1	1	2	2
[25]	1, 3, 4, 5, 6	1	2	1	2	1	1	1	1	1, 2, 3, 4, 5	1	2	2	1	1	2	1	1	1	1	2
[26]	2, 3, 4, 5	1	2	2	2	2	1	2	2	1, 2, 3, 4, 5	2	2	2	1	1	1	1	2	1	2	2
[27]	2, 3, 4, 5	1	2	1	2	1	2	2	1	1, 2, 3, 4, 5	1	2	1	1	1	1	1	1	1	2	2
[28]	1, 2, 3, 4, 5	1	2	1	2	1	2	2	1	1, 2, 3, 4, 5	1	2	2	1	1	1	1	2	1	2	1, 2
[29]	1, 2, 3, 4	1	2	1	2	1	2	2	2	1, 2, 3, 4, 6	2	2	1	2	2	2	2	2	2	2	2
[30]	1, 2, 3	1	2	1	2	2	1	1	2	1, 2, 3, 4, 6	1	2	2	1	1	1	2	2	2	1	1
[31]	1, 2, 3, 4, 5	1	2	1	2	1	2	2	2	1, 2	1	2	1	1	1	1	1	1	1	2	2
[32]	1, 2, 6	1	2	1	2	1	1	1	2	1, 2	2	2	2	2	2	1	1	1	1	2	2
[33]	1, 2, 3, 4, 5	1	2	2	2	1	1	1	2	1, 2	2	2	2	2	2	2	2	1	1	1	2
[34]	1, 2, 3, 4, 5	1	2	2	2	2	2	2	1	1, 2	1	2	2	1	2	2	1	2	1	1	2
[35]	2, 3, 4, 5, 6	1	2	1	2	2	1	2	2	1, 2	2	2	2	1	1	1	2	2	1	1	2
[36]	1, 2, 3, 4, 5	1	1	1	2	2	1	1	2	1, 6	2	2	2	2	2	2	2	1	1	1	1
[37]	1, 2, 3, 4, 5	2	1	1	1	2	2	2	2	1, 6	1	1	2	2	1	2	2	2	2	2	2
[38]	1, 3, 4, 5	1	2	1	2	1	1	1	1	2	1	2	2	2	1	2	2	2	2	2	2
[39]	1, 4, 5	1	2	1	2	1	2	1	1	1	2	2	2	1	1	2	1	1	1	2	1, 2
[40]	1, 2, 3, 4	1	2	1	1	2	1	2	1	1	2	2	1	1	1	2	1	2	1	2	2
[41]	2	1	2	2	2	2	2	2	1	1	2	2	2	1	2	2	1	1	1	2	2
[42]	1, 3, 4	1	2	1	2	1	2	2	1	1	1	2	2	2	2	2	2	2	2	2	2
[43]	2, 3, 4, 5	1	2	1	1	2	1	2	1	1	2	2	2	1	1	2	1	1	1	2	2
[44]	1, 2, 3, 4, 5	1	2	2	2	2	1	2	2	1	1	1	2	1	1	2	1	1	1	2	1, 2
[45]	2	1	2	2	2	1	2	2	2	1	1	1	2	2	1	1	2	1	1	2	1
[46]	2, 3, 4, 5	1	2	1	2	1	1	2	2	1	1	2	2	2	1	2	2	1	1	2	1
[47]	1, 2, 3, 4, 5	2	2	1	2	1	2	2	2	1	1	2	2	2	1	2	2	1	1	2	1, 2
[48]	1, 3, 5	1	2	1	2	2	1	2	1	1	2	1	1	1	1	2	1	1	1	2	2
[49]	1, 3, 4, 5	1	2	1	2	2	1	2	1	1	2	1	1	2	2	2	1	2	1	2	2
[50]	1, 3, 4, 5	1	2	1	2	1	2	2	1	1	2	1	2	2	2	2	2	2	1	2	1
[51]	1, 3, 4, 5	1	2	2	1	2	2	2	1	1	2	1	2	1	1	2	2	2	1	2	1, 2
[52]	1, 2, 3, 4	1	2	1	2	2	1	2	1	1, 5	1	1	2	1	1	1	2	1	1	2	1, 2

Legends		
Physical Infrastructure	**Bins Type**	Organic (1), Glass (2), Paper (3), Plastic (4), Metal (5), Toxic (6)
	Bins Location	Outdoors (1), Underground (2)
	Pneumatic Pipes	Incorporated (1), Not Incorporated (2)
	Fleet of Trucks	Homogenous (1), Heterogeneous (2)
	Depots	Incorporated (1), Not Incorporated (2)
	Dumps	Single (1), Multiple (2)
	Recycling	Supported (1), Not Supported (2)
	Processing	Supported (1), Not Supported (2)
IoT Technology	**RFIDs**	Incorporated (1), Not Incorporated (2)
	Sensors	Capacity (1), Weight (2), Temperature (3), Humidity (4), Chemical (5), Pressure (6)
	WSNs	Defined (1), Implied (2)
	Actuators	Incorporated (1), Not Incorporated (2)
	Cameras	Incorporated (1), Not Incorporated (2)
	GPS	Incorporated (1), Not Incorporated (2)

Software Analytics	**Architecture**	Defined (1), Implied (2)
	DSS	Incorporated (1), Not Incorporated (2)
	GIS	Incorporated (1), Not Incorporated (2)
	Dynamic Scheduling	Defined (1), Implied (2)
	Dynamic Routing	Defined (1), Implied (2)
	Social Context	Supported (1), Not Supported (2)
	Experimental Data	Synthetic (1), Real (2)

dynamic routing model which can handle real time routing requirements; while simultaneously encodes this knowledge to the upper tier enabling context pro-activeness. In [51], the authors have proposed a robust waste collection model exploiting cost efficiency of IoT potentiality in SCs. The research extends [50] by introducing a dynamic routing algorithm, which is robust and copes with cases of truck replacement due to overload or damage in the city of St. Petersburg in Russia. The paper presents a system model which incorporates two kinds of trucks for waste collection, the Low Capacity Trucks (LCTs) and the High Capacity Trucks (HCTs), respectively. The incorporation of HCTs achieves reduction of the waste collection operational costs because the route trips to the dumps are reduced due to the high waste storage capacity of these trucks. In [52], the authors have proposed an advanced DSS for efficient waste collection in SCs. The research extends [51] by introducing a model for on line data sharing between truck drivers in order to perform waste collection and dynamic route optimization. In addition, the system can handle various cases of ineffective waste collection in inaccessible areas within the SC. The system also incorporates surveillance cameras in order to capture problematic areas and provide evidence to the authorities.

The strengths and weaknesses of the aforementioned models are as follows:

- Model presented in [48]: the incorporation of novel classification models, which optimize and outperform research in [40], thus, enabling improved bin detection, monitoring and management. The model exploits data produced only from a specific type of capacity sensor.
- Model presented in [49]: the incorporation of cameras and the advanced classification process using DTW, which optimize and outperform research on image processing performed in [48]. The paper exploits data produced only from a specific type of capacity sensor.
- Model presented in [50]: it incorporates IoT Technology and a dynamic routing model. The model exploits data produced only from a specific type of capacity sensor.
- Model presented in [51]: the incorporation of a cost efficient heterogeneous fleet and the robust dynamic routing algorithm extending the research in [50]. The paper exploits data produced only from a specific type of capacity sensor.
- Model presented in [52]: it incorporates IoT Technology as well as an advanced DSS. However, the paper does not incorporate GIS as part of the advanced DSS.

3.3. Classification and Comparative Assessment

The summary of the comparative assessment performed on the survey is presented in Table 2. Thirty-two research efforts, in total, are reviewed and their strengths and weaknesses are revealed. Through the provided survey, we try to classify each model according to our taxonomy developed to depict important parts of the proposed systems. Concerning the physical infrastructure, organic bins are used in 22 models, glass bins in 20 models, paper bins in 25 models, plastic bins in 23 models, metal bins in 21 models and toxic bins in 4 models. Waste bins are located outdoors in 28 models while they are underground in 2 models. In just one model, bins are located both outdoors and underground. Pneumatic pipes are incorporated in 2 models, the fleet of trucks is homogenous in 22 models while it is heterogeneous in 9 models. Depots are incorporated in 6 models while they are absent in 25 models. Dumps are single in 18 models while they are multiple in 13 models. Recycling of inorganic waste is supported in 17 models and further processing of organic waste is supported in 8 models. The IoT Technology includes RFIDs (14 models), capacity sensors (30 models), weight sensors (12 models), temperature sensors (5 models), humidity sensors (6 models), chemical sensors (5 models) and pressure sensors (5 models). WSNs are adopted in 14 models and actuators are incorporated in 7 models. Cameras are incorporated in 6 models and GPS is incorporated in 16 models. In the category of software analytics, a DSS is incorporated in 9 models, GIS is discussed in 15 models, dynamic scheduling is defined in 16 models and dynamic routing is defined in 25 models. The social context is supported in 6 models. Synthetic experimental data are adopted for 7 models while real experimental data are adopted for the evaluation of 19 models. Moreover, 5 models are evaluated on both synthetic and real experimental data.

4. Conclusions and Future Work

This survey's focus is on more energy-efficient IoT as an enabler of various applications including waste management. Specifically, it aims to present a large set of models dealing with the efficient waste management. Special attention is paid on the waste collection. We present efforts for the intelligent transportation within the context of IoT and Smart Cities for waste collection. We propose an inductive taxonomy to perform comparative assessment of the surveyed models. We focus only on efforts that incorporate ICT models for waste collection in SC. We deliver the strengths and weaknesses of the surveyed models. Finally, our future work is focused on the definition of an effective IoT-enabled model for waste collection, which will touch on the incorporation of high capacity waste trucks as mobile depots. In addition, waste bins are placed to optimize comfort of residents. However, as part of the future work we will be looking at bin connectivity constraints that may affect their placement, for example, the output power of a communicating sensor would need to be set too high which may drain the battery faster. In this case, the bin may be placed somewhere where energy consumption is more efficient.

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