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Improving logistic efficiency of WEEE collection through dynamic scheduling using simulation modelling

Abstract

The complexity of collection systems for Waste from Electric and Electronic Equipment (WEEE) in the EU is increasing, due to the latest directive that sets new collection targets and modes. The high variability and the uncertainty of reverse flows require innovative logistic approaches. One recent option for increasing efficiency and responsiveness in waste collection services, boosted by new technological solutions for waste level monitoring, is to adopt a dynamic collection scheme, where the collection frequency is not established a priori (based on a fixed plan), but it is based on the actual filling levels of waste bins. This option can allow the service provider to plan the collection service following the actual demand, resulting in a more responsive service, while improving the logistic efficiency. This paper evaluates the implementation of dynamic scheduling schemes for the collection of WEEE. A hybrid simulation model has been developed in order to support researchers and practitioners in assessing quantitative impacts of adopting dynamic scheduling in WEEE collection. Three logistic alternatives (a fixed collection schedule scheme, a pure dynamic scheme and a mixed one) have been compared in a test case based on data of an Italian municipality; collection services for different types of WEEE (i.e. large appliances and small items) have been analyzed. Results show a promising performance of dynamic schedules compared to the fixed one, revealing, for the specific test case, how a mixed solution can combine the advantages of dynamic and fixed scheduling, gaining flexibility towards customer demand while improving truck resource utilization.

Keywords: e-waste collection; dynamic scheduling; simulation modelling; Pay-as-you-throw (PAYT).

1. Introduction

Waste from Electric and Electronic Equipment (WEEE) is one of the most critical waste flows worldwide. On one side, it is one of the fastest growing flows, since the volume of WEEE generated increases by a rate of 3-5% per year (Cucchiella et al., 2015). On the other side, products in the end-of-life stage contain precious materials that could be recovered, as well as hazardous substances that need to be treated and disposed properly (Mihai and Gnoni, 2016; Oliveira et al., 2012; Ongondo et al., 2011). Despite the Basel Convention treaty, the US and many European countries are exporting part of their WEEE to developing countries (mainly in Southeastern Asia and Africa), contributing to resource depletion and material loss for the exporter countries, while causing uncontrolled pollution and health issues related to a lack of waste valorization (Ongondo et al., 2011; Tansel, 2017). Recently, the European Union established new collection targets for the member States, passing from a fixed target (i.e. 4kg per inhabitant) (Directive 2002/96/EC) to a floating one proportional to the average quantity of EEE sold in the (three) previous years (Directive 2012/19/EU). This legislative change is forcing a strong increase in WEEE collection rate, which mainly depends on service efficiency. The adoption of new logistics models is essential to overcome some of the main criticalities related to WEEE collection. One recent solution, studied in some prototypal cases, is to transform the traditional (static) service approach into a Product-Service-System (PSS), where the service component (waste collection) is improved by a product component, i.e. technological solutions for waste monitoring and data transmission. This new approach could enable more dynamic collection schemes, in order to face the emerging complexity related to the management of highly variable waste flows. Specifically, a dynamic scheduling of the service, based on the actual level of waste produced monitored through sensors collecting real-time data, could be a valid alternative to the currently adopted fixed scheduling schemes, where the service is planned based on average demand forecast (Johansson, 2006).

This work analyzes the implementation of dynamic collection schemes for WEEE, comparing them with traditional fixed ones through simulation modelling. A dynamic collection scheme organizes collection frequency based on the actual level of bins; on the contrary, current collection services are often based on a fixed collection frequency set by an a priori service plan. The aim is to evaluate the technical efficiency of these new logistic models in collecting waste compared to traditional ones. A hybrid simulation model has been developed with this purpose.

The paper is structured as follows: a theoretical background is presented in Section 2. Section 3 describes the peculiarities of WEEE collection, with particular focus in the Italian system. Materials and methods are presented in Section 4, while results are discussed in Section 5. Section 6 summarizes the conclusions.

2. Theoretical background

2.1 Towards dynamic scheduling for waste collection

Collection and transportation are critical steps in a solid waste management system, both from an economic and environmental perspective, as they account for a consistent part of the total management costs and imply an intensive use of vehicles (Boskovic et al., 2016; Król et al., 2016; Zsigraiova et al., 2013). Therefore, new solutions that aim at increasing the efficiency and the environmental performance of the collection process, like PSS, could affect positively the overall sustainability of the waste management system. PSS has been defined as "a system of products, services, supporting networks and infrastructure that is designed to be competitive, satisfy customer needs and have a lower environmental impact than traditional business models". The adoption of PSS models in the public services sector is quite a recent approach: several benefits could be outlined starting from an increase in service efficiency to economic savings (Mont, 2002). Waste management represents an interesting public service where the adoption of PSS could make a relevant contribution, in particular in the collection phase. The implementation of PSS models in waste collection is mainly based on the diffusion of Internet of Things (IoT) in this sector. One example is the possibility provided by IoT devices to track the waste bin level, but also to identify the users of the waste collection service (Elia et al, 2015; Hannan et al., 2015). According to the type of waste flow and to local constraints and conditions, different technological solutions can be chosen: several prototypes for measuring the filling level of a bin and transmitting data to the service provider have been presented in literature, along with different solutions for the user identification (Anagnostopoulos et al., 2017). The massive diffusion of IoT technologies in the waste collection process will support more effective and efficient economic models, like the *Pay-As-You-Throw (PAYT) approach*, as well as innovative logistics models, like *dynamic scheduling*, which are implicitly connected. The basic idea derives from the PSS paradigm: the process has to be designed based on the actual demand of the user. Therefore, PAYT aims at charging the user proportionally to the service received, depending on the type and the quantity of the waste provided to the waste service (Bilitewski, 2008). According to scientific literature, this approach results in several advantages for the user, the service provider and the society. On one side, it would improve the equity of the system, since the user would pay a fee proportional to the effective use of the service. This could also promote virtuous behavior, with environmental and economic benefits related to the increase of recycling rate; however, this outcome can change from case to case, since it is strictly dependent on the public perception of the PAYT system implemented (Dahlén and Lagerkvist, 2010). Dunne et al. (2008) analyze this issue and suggest some guidelines to improve acceptability. On the other side, an effective design of the system would allow the service provider to benefit from the economic advantages related (Reichenbach, 2008).

Dynamic scheduling aims at organizing the collection frequency based on the actual filling level of the waste bin rather than on fixed dates, and it has recently become a topic of increasing interest for researchers and practitioners (Elia et al., 2015). Dynamic scheduling can extend the “Pay-As-You-Throw” logic to a “Pay-As-You-Use” one by performing the collection only when required (Elia et al., 2016). Waste measurement in the different collection points, required in a PAYT system, can be combined with real time data collection and update, allowing the service provider to know the actual state of the system, including data about which collection point is getting full and needs to be served first. This could heavily improve the overall collection efficiency, since the service adapts to the current demand, as opposed to traditional schemes with fixed scheduling based on forecasts usually estimated on average generation rates (Fig.1).

The focus of this study is to evaluate the technical convenience of adopting dynamic scheduling in waste collection from a logistics point of view.

[Insert Figure 1]

Figure 1: Transition from a fixed to a dynamic waste collection service.

2.2 Dynamic waste collection: a literature analysis

A literature analysis was performed to outline the state of the art about dynamic collection services in waste management. Recent studies deal with the *technological and organizational perspectives*, analyzing design issues or describing case studies. Thürer et al. (2016) analyzed the adoption of an IoT system for waste collection as a Kanban-based system, thus based on actual demand (the so called pull system) rather than on forecasts (as in traditional push systems). The Kanban method is a card-based inventory-control system usually applied in just-in-time manufacturing to manage pull production (Sugimori et al., 1977). The authors describe analogies and differences between Kanban for manufacturing processes and for reverse logistics, with a focus on the waste services. Anagnostopoulos et al. (2017) proposed a taxonomy for classifying intelligent waste management systems and their components, and used it to perform a literature analysis on IoT-based applications for waste management. Hannan et al. (2011) proposed a system based on different IoT technologies (RFID, GPS, GPRS and GIS) that helps monitoring the status of each bin, allowing to collect updated historical data for optimizing collection services. Similarly, Sharmin and Al-Amin (2016) described a cloud-based system for waste collection able to gather data about the bin weight and optimize the routing based on actual filling level; no comparisons with other approaches was proposed. Finally, Lindström et al. (2017) analyzed a collection model based on IoT technologies for dynamic scheduling, focusing on the description of the main organizational impacts for the provider, as well as advantages for the customers.

Other studies in the literature analyzed the implementation of dynamic scheduling focusing on the *economic advantages and efficiency* of these models, often compared to fixed ones. Johansson (2006) used analytical modeling and discrete events simulation (DES) to compare different scheduling and routing policies, based on real data from a Swedish solid waste management system with smart containers. Results showed the positive impact of adopting dynamic scheduling and routing for reducing operational cost in waste collection services in large areas; the benefit decreased for smaller contexts. Faccio et al. (2011) proposed an effective multi objective model integrated with traceability data, tested on an Italian municipality. Their analysis also included investment costs, demonstrating the economic feasibility of the system. Similarly, Anghinolfi et al. (2013) proposed a decision model for the dynamic optimization of materials collection in a waste management system, integrated with a GIS-based decision support tool; the model allowed an economic comparison between the fixed and dynamic services. Asimakopoulos et al. (2016) proposed a dynamic routing waste collection model, based on an IoT system that provides information about the fill level of the bins, showing through simulation how their solution outperforms the traditional fixed routing system. A similar system is presented by Borozdukhin et al. (2016), whose model also added data about traffic congestion to include time objectives in the routing problem. Another example of dynamic routing based on waste level monitoring is described by Mes et al. (2014): the authors discussed a case study in the Netherlands based on the adoption of a heuristic approach for the daily collection service planning, which was tested through a simulation model. Similarly, Gutierrez et al. (2015) discussed an IoT-based system allowing the waste collection firm to gather filling level data from the bins and to elaborate daily the most convenient route for collection. They compared this system with a fixed routing based on cluster zones and, unlike other studies, they reported that the higher collection efficiency obtained with the IoT system corresponds to higher total costs. This is also due to the estimation of high investment costs for the IoT infrastructure. Focusing on the technical performance, McLeod et al. (2014) applied a dynamic policy for the collection of charity assets from donation banks and retail shops, comparing its performance to the existing fixed scheduling scheme. The research showed that a minimum fill level between 50% and 75% allows time and distance savings up to 30%. Anagnostopoulos et al. (2015) discussed a dynamic waste collection model, which was applied only for high priority areas. Among several KPIs identified, the authors outlined a higher responsiveness of their solution (expressed as response time) compared to static models. Finally, Lelah et al. (2011) analyzed the environmental dimension of the problem applying life cycle assessment (LCA) to point out the main environmental impacts and benefits of dynamic scheduling in the glass collection service. A summary of the literature reviewed is shown in Table 1.

Table 1: Literature analysis about IoT for dynamic waste collection

#	Focus	Adopted methodology	Compare static and dynamic scheduling
Anagnostopoulos et al., 2017	Technological	Literature review	No
Hannan et al., 2011	Technological	--	No
Lindström et al., 2017	Organizational	--	No
Sharmin and Al-Amin, 2016	Efficiency	--	No
Thürer et al., 2016	Model architecture	Conceptual study	No
Anagnostopoulos et al., 2015	Efficiency	Simulation	No
Anghinolfi et al., 2013	Economic	Dynamic modelling + GIS	Yes
Asimakopoulos et al., 2016	Economic	Simulation	Yes
Borozdukhin et al., 2016	Economic + Efficiency	Real case	Yes
Faccio et al., 2011	Efficiency	Multi objective model	Yes
Gutierrez et al., 2015	Economic + Efficiency	Simulation (GIS)	Yes
Johansson, 2006	Economic	Analytical model + simulation (DES)	Yes
Lelah et al., 2011	Environmental	LCA	No

McLeod et al., 2014	Economic + Efficiency	Analytical model	Yes
Mes et al., 2014	Economic	Simulation optimization (DES)	Yes

2.3 Discussion and scope of the work

Some considerations can be derived from the literature analysis previously discussed.

- The increasing diffusion of IoT technologies is a new issue in waste management: its main contribution could be to enable efficiently dynamic scheduling collection systems. Few recent studies have faced this topic, especially from a technological and organizational perspective; the evaluation of its feasibility from a logistics point of view compared to traditional models has not yet been fully analyzed. The focus of the works considered is often on the technological and organizational perspective; few papers analyze the economic performance and efficiency of the new logistics model, outlining potential benefits compared to traditional ones.
- Analyzing the methodologies adopted in these studies, either analytical or simulation models are used to evaluate system performance from different points of view. Most of the studies outlined some benefits in costs or efficiency of the dynamic collection scheme compared to the fixed one. Only two studies (Gutierrez et al., 2015; Johansson, 2006) highlighted some criticalities, i.e. a cost increase, also due to the initial investments, and the influence of the demand *variability* and the *size* of collection area on the system efficiency. This suggests that further investigation is needed.
- Most of the studies analyzed apply dynamic schemes to Municipal Solid Waste (MSW) collection. Only four papers considered more specific applications, like glass collection, high priority waste, charity assets and WEEE (Anagnostopoulos et al., 2015; Elia et al., 2016; McLeod et al., 2014; Lelah et al., 2011), despite the wide potential of waste collection “as-a-service” for commercial users (retailers, shops, etc.), not only for citizens. Evaluating the implementation of this model to other waste flows is still an unexplored issue.

This work contributes by exploring the impact of dynamic scheduling applied to waste collection systems for commercial users in a MSW system, through simulation modelling, aligning with the latest research on the topic. Particularly, the aim is to explore the application of this model to waste flows different from MSW (i.e. collected from commercial users), and verify the efficiency and economic implications related to the transition from a fixed service (based on a constant collection frequency) to a dynamic one (based on a variable collection frequency). Specifically, the case of WEEE collected by retailers in an Italian municipality has been studied: WEEE collection services typically differ from other MSW collection services due to several issues, which are discussed in the following section.

3. The test case: WEEE collection

In this section, the main issues regarding WEEE flows and current organization of collection services are analyzed. The WEEE is one of the fastest growing flows worldwide. The estimated world production of WEEE in 2014 was of about 41.8 Mt, of which about 6.5 Mt collected and treated by formal national take-back systems, while the forecasted growth rate is of 4-5% per year until 2018 (Baldé, 2015), which is about three times the growth of MSW flows (Duygan and Meylan, 2015). The importance of this waste flow is also related to the composition of end-of-life products, which contain high value materials, as well as hazardous substances (Elia and Gnoni, 2015; Mihai and Gnoni, 2016). The collection service represents the first critical process to design in order to prevent environmental damages caused by an incorrect management of WEEE. Therefore, most legislations and guidelines about WEEE management focus on collection targets; some of them are being updated worldwide, aiming at facilitating material recovery and diversion from landfills and illegal export to developing countries. The EU issued a new directive (Directive 2012/19/EU) aiming to align the European WEEE collection service to current market dynamics (De Felice et al., 2014). An important innovation affects the collection target: it has been modified from a previous fixed amount (4 kg per inhabitant per year) for all EU countries to a “floating” target estimated based on a percentage (45% in 2016, 65% by 2019) of the EEE sold in the three previous years in each EU country. Another innovation regards the collection methods available for waste collection users: the previous well-known "*one-to-one*" service (allowing customers to give back to the retailer an old EEE when buying a new one) has been integrated with the so called "*one-to-zero*" model. This one forces retailers to provide also the collection of small WEEE for users, even when they do not buy a new product. Both these innovations aim at increasing the quantities of WEEE collected through reverse logistics systems, which need to be more responsive and efficient in satisfying the demand. Moreover, the variability of the quantities to be collected at the retailer's facilities will most likely increase: the introduction of the "*one-to-zero*" solution adds a further source of uncertainty to the waste generation rate, highly influenced by an unpredictable customers' behavior.

All these factors require new reverse logistics models, which have to be flexible and effective to satisfy the demand, but also responsive to face all the increased uncertainties (Mihai and Gnoni, 2016). As mentioned in Section 2, fixed schedules are planned considering the forecasted demand based on average historical data (Fig. 1). Uncertainties due to the introduction of the new "one-to-zero" collection service can sensitively decrease the effectiveness of such forecasts, adding variability to the already hardly predictable WEEE flow. A dynamic collection scheme based on waste monitoring and enabled through a PSS solution could allow a higher responsiveness of the system while increasing the logistic efficiency, and needs to be further explored.

3.1 The WEEE collection system in Italy

Like in most European countries, there is a dual channel for WEEE collection services in Italy. One is carried out by the local MSW collection service provider, which usually includes fixed collection points where the user can bring WEEE (Favot et al., 2016). The other one is carried out directly by EEE retailers, which have to collect waste from customers when requested, through the "one-to-one" and the "one-to-zero" modes, as regulated by the European directive (Fig. 2). Five groups of WEEE are defined by the Italian legislation, which includes bulky wastes (i.e. from white and brown goods) as well as small items, like PCs or mobile phones. Each retailer can collect all these categories or only a part, according to the size of its retail area. Retailers could preliminary stock the WEEE collected, although the quantity stored cannot exceed the weight of 3.5 tons. Thus, they have to organize the collection service with a certified transport service provider company that moves their WEEE to recycling facilities. Planning this service is not a simple issue, as on one side it has to guarantee the strict respect of the maximum stocking quantity defined by law; on the other side, aiming to respect this limit, retailers have a tendency to plan a high collection frequency for facing uncertainties, thus determining higher service costs. The low predictability of customers' behavior increases the uncertainty of return flows, resulting in a high variability of the demand for the collection service (Elia and Gnoni, 2015) as depicted in Figure 2.

[Insert Figure 2]

Figure 2: Actors and flows of WEEE collection systems in Italy

Therefore, there is need for effective collection models that can provide service continuity while ensuring economic sustainability for the retailers. In the following sections, different collection service alternatives (based on a fixed and a dynamic frequency) are described for WEEE collection in a Southern Italy municipality; a simulation based tool has been developed to assess their technical performance aiming to support an effective design of the WEEE collection service.

4. Materials and methods

In this section, the methodology adopted for the analysis is presented.

Hybrid simulation modelling allows combining the main strengths and benefits of different simulation modeling techniques (i.e. Discrete Event Simulation, System Dynamics, Agent Based Modeling) (Lättilä et al., 2010). Recent research shows how this approach can be effective in the design and management of PSS solutions (Rondini et al., 2017). Therefore, a hybrid simulation model has been developed to compare different collection schemes in a test case applied in the city of Lecce (Italy). Since the purpose of this work is to analyze the efficiency and effectiveness of different approaches, a sample of EEE retailers present in the municipal area has been considered (Fig. 3). The analysis involves two types of retailers: five *big* EEE stores, which have to collect all WEEE categories from customers, and ten *small* retailers, who sell only one EEE typology (i.e. lighting devices) and shall collect only this type of waste. For this last case, we have assumed a maximum storage capacity of each small retailer (equal to 30 kg) based on current experience deducted from the field. This limit is not established by the Italian law, but it represents a reasonable amount of these items to collect even for small retailers.

[Insert Figure 3]

Figure 3: Location of the big (green) and small (orange) retailers in the area considered in the GIS environment.

For each retailer, the process of WEEE generation has been simulated through S*ystem Dynamics* (SD) modeling technique (Forrester, 1961) based on stocks (levels) and flows (rates) logic. Each WEEE deposit (see Fig. 4) is modelled by a stock, which is fed by a rate calculated as the sum of the “one-to-zero” and the “one-to-one” components, both weighted by a zone coefficient. This latter has been modeled through a Pert distribution, with different values for each retailer depending on specific location factors (e.g. its position, its retail extension). The “one-to-one” component has been considered as 45% of the EEE sales, assuming that the minimum target established by law would be reached (see Equation 1). The stock is emptied every time a collection activity occurs.

$$WEEEstock = ZC_{10} * oneToZero + 45\%(ZC_{11} * sales) \quad (1)$$

[Insert Figure 4]

Figure 4: WEEE estimation model logic developed with System Dynamics simulation.

Data about EEE sales, used in the System Dynamics model, have been derived from national reports (CdC RAEE, 2016, 2015, 2014) based on average values of the last three years (2013-2015), which are now available. Furthermore, sales for the city of Lecce have been estimated based on its current population starting from national data. All sales intercepted by the analyzed retailers represent 50% of the total sales in the municipality: this assumption is based on the extension of their retail area. These data, together with the ones used for estimating the zone coefficients in equation 1, are reported in the Appendix (Tables A.1, A.2, A.3 and A.4).

The routing process in the collection service has been simulated adopting *Agent Based Modeling* (ABM) simulation technique, moving in a *Geographic Information System* (GIS) environment. For *big* retailers, a dedicated truck is used for each customer, given the quantity of WEEE to collect (about 3.5 tons per trip). For *small* retailers, a truck is used to serve different customers. Every time a service order is generated, the truck starts its collection trip and serves the customers, according to the collection scheme considered. Once the truck is at the customer's location, a *Discrete Events Simulation* (DES) module simulates the collection process. After the service is completed, the truck brings the e-waste collected to the treatment (recovery) plant. For both *big* and *small* retailers, the critical levels are calculated considering a safety period before reaching the maximum level, which is three days for the fixed schedule and one day for the dynamic schedule, based on the average daily quantity of WEEE collected (45% of forecasted sales).

The simulation time has been set at six months. For each scenario, twenty replications per instance were run, giving a confidence level of 95%.

Three design alternatives for WEEE collection have been considered: Alternative 1 (A1), Alternative 2 (A2), Alternative 3 (A3). A1 consists of a collection service with ***fixed schedule (i.e. collection frequency)*** both for big and small retailers; emergency extra calls (with increased costs) could be required by the retailer when the level of WEEE reaches unexpectedly a critical threshold. This first scheme is the one currently applied by retailers, thus representing the baseline for a comparison with innovative approaches. A2 consists of a ***dynamic schedule*** based on variable collection frequency: WEEE level is monitored in real time and the collection service is performed when the bin level reaches a critical threshold limit. The service provider has defined a specific rule for small retailers: when one user reaches the critical level, all other users are checked and the collection service is performed only for those who exceed the minimum collection level of 70%. This value has been set considering both field experience and data discussed by McLeod et al. (2014), where the authors reported that the dynamic collection system reached the best performance when the collection target was set between 50% and 75% of the maximum filling level. A3 consists of a ***mixed solution*** considering a different rule for small retailers under a dynamic collection service: every time one user activates the call, all customers are served regardless of their filling level.

To assess the efficiency of the collection service, the following Key Performance Indicators (KPIs) have been adopted:

i. the number of collection services performed for small and big retailers;
ii. the number of emergency services performed (only for A1);
iii. the total distance in km covered by the collection trucks for small and big retailers;
iv. the average, maximum and minimum filling level of the truck for small retailers.

Moreover, the total amount of WEEE collected has been monitored.

A first experiment (experiment 1) compares the alternatives as previously described; then, a sensitivity analysis considering different values for some design parameters under both alternatives is performed.

5. Results and discussion

5.1 Experiment 1

The results of the simulation for experiment 1 are reported in Table 2, along with the variation of KPIs given by alternatives A2 and A3 compared to the baseline (A1).

The first result to highlight is the drastic decrease in the number of collection services performed in six months. For big retailers, the total number of services decreases of about 36% adopting A2 and A3 scenarios: this is mainly due to the elimination of extra calls, as all calls are performed "on request". It has to be noted that, even excluding the extra calls performed, more collection services are still scheduled in the baseline (46 on average) than in both dynamic scenarios (33 on average). Consequently, the estimated total distance decreases also by about 37%. A similar outcome can be observed for small retailers, where A2 and A3 scenarios present a better performance. The number of collection services decreases by more than half in A2 (from about 56 of A1 to 25), with corresponding distance savings of almost 54% compared to the baseline. A higher efficiency can be observed with A3, where the estimated number of services decreases heavily as the average value is equal to 10 (80% lower than the baseline). In this case, the average distance decreases by almost five times, reaching the absolute minimum value of about 580 km. Therefore, based on estimated results and under these assumptions, the mixed solution seems to be the most efficient collection service scenario in terms of technical efficiency. This is confirmed considering the utilization of the truck: while there is a range of about 150 kg of difference between the maximum and minimum filling levels observed for both the fixed (A1) and the dynamic schedule (A2), the mixed solution (A3) allows a more homogeneous use of the resource, with a range of only 35 kg and an average of 218 kg, which is about five times higher than the average in alternative A1.

A1 is the worst scenario for both big and small retailers, mainly due to the high number of extra services required. This is related to the uncertainty (in terms of both quantity and time) introduced by the simultaneous presence of “one-to-one” and “one-to-zero” collection components.

Table 2: Simulation results of experiment 1 and % variation of KPIs (alternatives A2 and A3 compared to A1).

		A1 - Fixed schedule		**A2 - Dynamic schedule**			**A3 – Mixed solution**		
		Mean	**St.dev.**	**Mean**	**St.dev.**	**Δ% compared to A1**	**Mean**	**St.dev.**	**Δ% compared to A1**
Big retailers	WEEE quantity [kg]	110,628.90	713.99	112,384.03	3348.18	+1.6%	112,727.99	2313.83	+1.9%
	N° collections	52.35	2.21	33.45	1.00	-36.1%	33.50	0.69	-36.0%
	N° extra calls	6.35	2.21	--	--	-100.0%	--	--	-100.0%
	Tot distance travelled [km]	2,585.82	110.51	1,629.17	48.80	-37.0%	1,634.50	33.61	-36.8%
Small retailers	WEEE quantity [kg]	2,191.20	18.53	2,075.20	31.37	-5.3%	2,129.59	70.09	-2.8%
	N° collections	55.90	2.13	24.65	1.79	-55.9%	9.75	0.44	-82.6%
	N° extra calls	48.90	2.13	--	--	-100.0%	--	--	-100.0%
	Tot distance travelled [km]	2896.75	107.87	1342.09	90.53	-53.7%	582.61	26.55	-79.9%
	Average truck filling [kg]	39.25	1.32	84.77	6.27	+116.0%	218.58	4.87	+456.9%
	Max truck filling [kg]	171.29	10.25	163.32	27.29	-4.7%	234.90	5.80	+37.1%
	Min truck filling [kg]	27.05	0.01	29.22	6.68	+8.0%	200.31	8.15	+640.5%

5.2 Sensitivity analysis: Experiment 2

To explore the potentialities of the simulation tool in the design of a collection system, a sensitivity analysis has been performed in experiment 2. Different design parameters have been set for alternatives A1 and A2 in order to evaluate their new performance compared to the best outcome of experiment 1 (i.e. A3). The purpose is to outline the potentialities of the developed simulation model.

An improved scheduling policy has been tested for A1 (A1.1), increasing the collection frequency by considering the average demand plus a safety level (equal to 10%) for both big and small retailers, aiming to respond to the fluctuations given by the “one-to-zero” component of the demand.

For A2, a change in the threshold critical value has been introduced: the control level has been decreased from 70% to 50% (A2.1) in order to point out the impact of this variation. Results of experiment 2 are reported in Table 3.

Results show that A1.1 performs globally better than A1 as the estimated number of emergency services requested for big retailers is zero, and it also slightly decreases for small retailers. However, this improvement is not sufficient to reach the performance of A3 scenario: as reported in Table 3, A1.1 still presents a higher number of performed services, both for big retailers (+52.2%) and small ones (+421.5%), resulting in a longer distance covered by the operating trucks (about +54% and +352% for big and small retailers respectively). Although the quantitative results obtained in our test case cannot be extended to other cases, an interesting point has to be noted: even when forecast values about waste generation flows in fixed schedule policy are improved considering the “one-to-zero” component of the demand, its overall technical performance does not reach the efficiency of a dynamic solution. This is also confirmed by the resource utilization value of small trucks, which presents a range of 140 kg in A1.1, compared to 35 kg in A3, thus confirming the results of experiment 1.

Table 3: Simulation results of experiment 2 and % variation of KPIs (alternatives A1.1 and A2.1 compared to A3).

		A1.1 - Fixed schedule NEW			**A2.1 - Dynamic schedule NEW**		
		Mean	**St.dev.**	**Δ% compared to A3**	**Mean**	**St.dev.**	**Δ% compared to A3**
Big retailers	WEEE quantity [kg]	111,398.02	849.28	-1.2%	112,720.42	2,526.53	No variation
	N° collections	51.00	0.00	+52.2%	33.50	0.76	No variation

	N° extra calls	0.00	0.00	--	--	--	--
	Tot distance travelled [km]	2,520.94	0.00	+54.2%	1,633.38	36.87	-0.1%
Small retailers	WEEE quantity [kg]	2,012.48	32.77	-5.5%	2,093.22	55.80	-1.7%
	N° collections	50.85	2.36	+421.5%	13.25	2.61	+35.9%
	N° extra calls	43.85	2.36	--	--	--	--
	Tot distance travelled [km]	2,632.67	121.31	+351.9%	766.10	137.30	+31.5%
	Average truck filling [kg]	39.74	1.74	-81.8%	164.17	33.56	-24.9%
	Max truck filling [kg]	167.87	4.41	-28.5%	224.06	15.69	-4.6%
	Min truck filling [kg]	27.05	0.01	-86.5%	88.89	62.41	-55.6%

Similar considerations can be derived for A2.1. This solution performs better than A2 for small retailers, decreasing the number of services (-46%) and the distance covered (-43%). On the other side, A2.1 presents an increase of about +36% for the number of collection services and +31.5% for the distance travelled compared to A3, which is still the best solution. Moreover, the range of the filling level for the truck is still 135 kg, indicating a resource use not as efficient as in A3.

5.3 Discussion

While literature suggests that dynamic scheduling could be a successful strategy to improve the efficiency of waste collection systems, the experiments run show that pure dynamic models may not always be the best solution. In the case considered, the mixed model has the best performance, exploiting the advantages of the two pure alternatives. On one side, the real time data collected through IoT technologies allow the service provider to collect waste when at least one customer actually needs to be served, answering to the necessity of the demand, which is highly unpredictable for WEEE. On the other side, the increased sharing of the resource (truck), similar to the fixed schedule solution, allows a higher utilization rate, decreasing transportation costs and pollutant emissions, which are related to the distance covered (Zsigraiova et al., 2013). Moreover, results demonstrate the efficacy of the proposed hybrid simulation model to evaluate quantitatively different design alternatives and assess the efficiency of dynamic solutions compared to traditional ones. The adopted KPIs are related to the technical performance of the analysed alternatives; they could also be adopted as an indirect measure to estimate economic and environmental outcomes. However, some criticalities and limitations have to be underlined. As specified in section 4, this test case is based on a sample of retailers in the municipal area. No data about the collected WEEE per retailer are still available to validate quantitatively the results obtained. Moreover, no historical data are yet available about the incidence of the “one-to-zero” component on the WEEE flow, which is unpredictable for its nature and strongly dependent on the behaviour of citizens. Under these conditions, the simulation model has provided quantitative results with considerations that could be used in the preliminary design of new collection services for WEEE. Results from experiment 2 show that improving the forecasts of WEEE flows can allow a better planning of the fixed schedule. However, without consolidated knowledge about the “one-to-zero” flows, reaching a high reliability of predictions represents a very difficult task even for retailers, which should be considered when designing a collection service. Thus, despite the lack of accurate data for a complete simulation validation, we can outline that the potential benefits provided by dynamic scenarios (pure dynamic or mixed one) can be higher than traditional fixed schedule schemes as they can adapt better to demand fluctuations.

From a theoretical perspective, the application of PSS models in waste collection and management has to be deeper analysed. Literature about PSS mostly focuses on the transition from product to PSS through the servitization process, while the advantages related to the adoption of PSS in service sectors is still largely unexplored. Therefore, further research could aim at understanding the challenges and opportunities related to these innovative business models in the waste sector.

6. Conclusions

Recent European directive sets new collection targets and rules for WEEE. The “floating” target proportional to EEE put on market and the introduction of the “one-to-zero” component increase the variability of the flow over time while decreasing the effectiveness of forecast methods to assess the demand of collection service from users.

This work is an attempt to explore new approaches to the design of WEEE collection schemes. Two innovative alternatives based on PSS solutions that enable dynamic scheduling are described and compared to the traditional fixed schedule scheme, widely adopted by service providers especially for commercial users (e.g. retailers) in a MSW system. The collection service alternatives have been compared through a hybrid simulation model (based on GIS, DES, SD and ABM modules) that allows estimating selected KPIs. Results of the test case show that dynamic collection services perform better than traditional fixed ones, allowing essentially a higher flexibility of the service, which could fit better the fluctuations of customers' demand. This is a critical point: after the adoption of the new EU directive, further research is needed on the collection and analysis of data about WEEE generation and collection, especially related to the "one-to-zero" component. Moreover, an increased resource utilization can generate savings to customers also from an economic and environmental point of view. Further developments could be oriented to introduce also the impact due to high investment costs connected to the adoption of a dynamic collection service compared to traditional schemes, in order to assess the overall economic feasibility and sustainability of these models. Finally, research could focus on defining a general framework for the adoption of PSS in the waste management sector, studying the benefits and barriers related.

References

Anagnostopoulos, T., Kolomvatsos, K., Anagnostopoulos, C., Zaslavsky, A., Hadjiefthymiades, S., 2015. Assessing dynamic models for high priority waste collection in smart cities. J. Syst. Softw. 110, 178–192. doi:10.1016/j.jss.2015.08.049

Anagnostopoulos, T., Zaslavsky, A., Kolomvatsos, K., Medvedev, A., Amirian, P., Morley, J., Hadjiefthymiades, S., 2017. Challenges and Opportunities of Waste Management in IoT-enabled Smart Cities: A Survey. IEEE Trans. Sustain. Comput. 1–1. doi:10.1109/TSUSC.2017.2691049

Anghinolfi, D., Paolucci, M., Robba, M., Taramasso, A.C., 2013. A dynamic optimization model for solid waste recycling. Waste Manag. 33, 287–296. doi:10.1016/j.wasman.2012.10.006

Asimakopoulos, G., Christodoulou, S., Alefragis, P., Gizas, A., Triantafillou, V., 2016. Dynacargo: The evaluation results of a Dynamic Waste Collection Management System based on Real-time and Forecasted Data. ACM Press, pp. 1–5. doi:10.1145/3003733.3003804

Baldé, K., 2015. The global e-waste monitor 2014 quantities, flows and resources. United Nations Univ., Inst. for the advanced study on sustainability, Bonn.

Bilitewski, B., 2008. From traditional to modern fee systems. Waste Manag. 28, 2760–2766. doi:10.1016/j.wasman.2008.03.032

Borozdukhin, A., Dolinina, O., Pechenkin, V., 2016. Approach to the garbage collection in the “Smart Clean City” project. IEEE, pp. 918–922. doi:10.1109/CIST.2016.7805019

Boskovic, G., Jovicic, N., Jovanovic, S., Simovic, V., 2016. Calculating the costs of waste collection: A methodological proposal. Waste Manag. Res. 34, 775–783. doi:10.1177/0734242X16654980

CdC RAEE, 2016. Rapporto annuale 2015 - Ritiro e trattamento dei rifiuti da apparecchiature elettriche ed elettroniche in Italia.

CdC RAEE, 2015. Rapporto annuale 2014 - Ritiro e trattamento dei rifiuti da apparecchiature elettriche ed elettroniche in Italia.

CdC RAEE, 2014. Rapporto annuale 2013 - Ritiro e trattamento dei rifiuti da apparecchiature elettriche ed elettroniche in Italia.

Cucchiella, F., D'Adamo, I., Lenny Koh, S.C., Rosa, P., 2015. Recycling of WEEEs: An economic assessment of present and future e-waste streams. Renew. Sustain. Energy Rev. 51, 263–272. doi:10.1016/j.rser.2015.06.010

Dahlén, L., & Lagerkvist, A. 2010. Pay as you throw: strengths and weaknesses of weight-based billing in household waste collection systems in Sweden. Waste Manag., 30(1), 23-31. doi:10.1016/j.wasman.2009.09.022

De Felice, F., Elia, V., Gnoni, M.G., Petrillo, A., 2014. Comparing environmental product footprint for electronic and electric equipment: a multi-criteria approach. Int. J. Sustain. Eng. 7, 360–373. doi:10.1080/19397038.2013.865811

Directive 2002/96/EC. Directive 2002/96/EC of the European Parliament and of the Council of 27 January 2003 on waste electrical and electronic equipment (WEEE). url: http://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:32002L0096

Directive 2012/19/EU. Directive 2012/19/EU of the European Parliament and of the Council of 4 July 2012 on waste electrical and electronic equipment (WEEE). url: http://eur-lex.europa.eu/legal-content/EN/TXT/?uri=celex:32012L0019

Dunne, L., Convery, F., Gallagher, L. 2008. An investigation into waste charges in Ireland, with emphasis on public acceptability. Waste Manag., 28 (12), 2826–2834. doi: 10.1016/j.wasman.2008.07.007

Duygan, M., Meylan, G., 2015. Strategic management of WEEE in Switzerland—combining material flow analysis with structural analysis. Resour. Conserv. Recycl. 103, 98–109. doi:10.1016/j.resconrec.2015.06.005

Elia, V., Gnoni, M.G., 2015. How to design and manage WEEE systems: a multi-level analysis. Int. J. Environ. Waste Manag. 15, 271. doi:10.1504/IJEWM.2015.069165

Elia, V., Gnoni, M.G., Tornese, F., 2016. Assessing the Efficiency of a PSS Solution for Waste Collection: A Simulation Based Approach. Procedia CIRP 47, 252–257. doi:10.1016/j.procir.2016.03.086

Elia, V., Gnoni, M.G., Tornese, F., 2015. Designing Pay-As-You-Throw schemes in municipal waste management services: A holistic approach. Waste Manag. 44, 188–195. doi:10.1016/j.wasman.2015.07.040

Faccio, M., Persona, A., Zanin, G., 2011. Waste collection multi objective model with real time traceability data. Waste Manag. 31, 2391–2405. doi:10.1016/j.wasman.2011.07.005

Favot, M., Veit, R., Massarutto, A., 2016. The evolution of the Italian EPR system for the management of household Waste Electrical and Electronic Equipment (WEEE). Technical and economic performance in the spotlight. Waste Manag. 56, 431–437. doi:10.1016/j.wasman.2016.06.005

Forrester, J.W., 1961. Industrial Dynamics. MIT Press, Cambridge, MA, reprinted by Productivity Press (1994) and now available from Pegasus Communications, Waltham, MA, USA.

Gutierrez, J.M., Jensen, M., Henius, M., Riaz, T., 2015. Smart Waste Collection System Based on Location Intelligence. Procedia Comput. Sci. 61, 120–127. doi:10.1016/j.procs.2015.09.170

Hannan, M.A., Abdulla Al Mamun, M., Hussain, A., Basri, H., Begum, R.A., 2015. A review on technologies and their usage in solid waste monitoring and management systems: Issues and challenges. Waste Manag. 43, 509–523. doi:10.1016/j.wasman.2015.05.033

Hannan, M.A., Arebey, M., Begum, R.A., Basri, H., 2011. Radio Frequency Identification (RFID) and communication technologies for solid waste bin and truck monitoring system. Waste Manag. 31, 2406–2413. doi:10.1016/j.wasman.2011.07.022

Johansson, O.M., 2006. The effect of dynamic scheduling and routing in a solid waste management system. Waste Manag. 26, 875–885. doi:10.1016/j.wasman.2005.09.004

Król, A., Nowakowski, P., Mrówczyńska, B., 2016. How to improve WEEE management? Novel approach in mobile collection with application of artificial intelligence. Waste Manag. 50, 222–233. doi:10.1016/j.wasman.2016.02.033

Lättilä, L., Hilletofth, P., Lin, B. 2010. Hybrid Simulation Models – When, Why, How? Expert Syst. Appl. 37 (12), 7969–75. doi:10.1016/j.eswa.2010.04.039.

Lelah, A., Mathieux, F., Brissaud, D., 2011. Contributions to eco-design of machine-to-machine product service systems: the example of waste glass collection. J. Clean. Prod. 19, 1033–1044. doi:10.1016/j.jclepro.2011.02.003

Lindström, J., Hermanson, A., Hellis, M., Kyösti, P., 2017. Optimizing Recycling Management Using Industrial Internet Supporting Circular Economy: A Case Study of an Emerging IPS 2. Procedia CIRP 64, 55–60. doi:10.1016/j.procir.2017.03.072

McLeod, F., Erdogan, G., Cherrett, T., Bektas, T., Davies, N., Shingleton, D., Speed, C., Dickinson, J., Norgate, S., 2014. Improving collection efficiency through remote monitoring of charity assets. Waste Manag. 34(2), 273-280. doi:10.1016/j.wasman.2013.11.006

Mes, M., Schutten, M., Rivera, A.P., 2014. Inventory routing for dynamic waste collection. Waste Manag. 34, 1564–1576. doi:10.1016/j.wasman.2014.05.011

Mihai, F.-C., Gnoni, M.-G., 2016. E-waste Management as a Global Challenge (Introductory Chapter), in: Mihai, Florin-Constantin (Ed.), E-Waste in Transition - From Pollution to Resource. InTech.

Mont, O., 2002. Clarifying the concept of product–service system. J. Clean. Prod. 10, 237–245. doi:10.1016/S0959-6526(01)00039-7

Oliveira, C.R. de, Bernardes, A.M., Gerbase, A.E., 2012. Collection and recycling of electronic scrap: A worldwide overview and comparison with the Brazilian situation. Waste Manag. 32, 1592–1610. doi:10.1016/j.wasman.2012.04.003

Ongondo, F.O., Williams, I.D., Cherrett, T.J., 2011. How are WEEE doing? A global review of the management of electrical and electronic wastes. Waste Manag. 31, 714–730. doi:10.1016/j.wasman.2010.10.023

Reichenbach, J., 2008. Status and prospects of pay-as-you-throw in Europe – A review of pilot research and implementation studies. Waste Manag. 28, 2809–2814. doi:10.1016/j.wasman.2008.07.008

Rondini, A., Tornese, F., Gnoni, M.G., Pezzotta, G., Pinto, R., 2017. Hybrid simulation modelling as a supporting tool for sustainable product service systems: a critical analysis. Int. J. Prod. Res. 1–14. doi:10.1080/00207543.2017.1330569

Sharmin, S., Al-Amin, S.T., 2016. A Cloud-based Dynamic Waste Management System for Smart Cities. ACM Press, pp. 1–4. doi:10.1145/3001913.3006629

Sugimori, Y., Kusunoki, K., Cho, F., Uchikawa, S., 1977. Toyota production system and Kanban system Materialization of just-in-time and respect-for-human system. Int. J. Prod. Res. 15(6), 553-564. doi: 10.1080/00207547708943149

Tansel, B., 2017. From electronic consumer products to e-wastes: Global outlook, waste quantities, recycling challenges. Environ. Int. 98, 35–45. doi:10.1016/j.envint.2016.10.002

Thürer, M., Pan, Y.H., Qu, T., Luo, H., Li, C.D., Huang, G.Q., 2016. Internet of Things (IoT) driven kanban system for reverse logistics: solid waste collection. J. Intell. Manuf. doi:10.1007/s10845-016-1278-y

Zsigraiova, Z., Semiao, V., Beijoco, F., 2013. Operation costs and pollutant emissions reduction by definition of new collection scheduling and optimization of MSW collection routes using GIS. The case study of Barreiro, Portugal. Waste Manag. 33, 793–806. doi:10.1016/j.wasman.2012.11.015

Appendix

Table A.1. Data about EEE sold in Italy and Lecce per year (2013-2015)

Year	EEE sold in Italy (tons)	EEE sold in Lecce (estimated tons)
2013	736625.5	1142.8

2014	804452.9	1248.0
2015	794897.0	1233.2
Average	*778658.5*	*1208.0*

Table A.2. Distributions adopted to model waste flows.

Flow	**Distribution adopted in S1 [kg/h]**	**Distribution adopted in S2 [kg/h]**
Sales for big retailers	Uniform(10, 18)	Pert(8, 22, 14)
1to0 for big retailers	Uniform (0.1, 0.5)	Pert(0.1, 2, 0.3)
Sales for small retailers	Uniform(0, 0.2)	Pert(0, 0.3, 0.1)
1to0 for small retailers	Uniform (0, 0.04)	Pert(0, 0.04, 0.02)

Table A.3. Mode of the zone coefficients used for big retailers (Ret).

	Ret 1	**Ret 2**	**Ret 3**	**Ret 4**	**Ret 5**
Mode of zone coefficient (1to0)	1	0,9	0,7	0,6	0,6
Mode of zone coefficient (1to1)	1	0,8	0,7	0,6	1

Table A.4. Mode of the zone coefficients used for small retailers (Sr).

	Sr 1	**Sr 2**	**Sr 3**	**Sr 4**	**Sr 5**	**Sr 6**	**Sr 7**	**Sr 8**	**Sr 9**	**Sr 10**
Mode of zone coefficient (1to0)	1	0,4	0,4	0,8	0,5	0,9	0,7	1	0,6	0,4
Mode of zone coefficient (1to1)	1	0,9	1	0,8	0,6	0,7	0,9	0,8	0,8	0,5