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DSS APPLICATIONS

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Decision support for optimizing waste management

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ABSTRACT

During the last few decades, research into sustainability aspects of ICT grew rapidly for most organisational and business processes. Evolution towards the development of infrastructure for Smart Cities, Green ICT with application of decision support systems (DSSs) created opportunities for solving complex problems, for example, sensor-enabled smart waste management. This paper focuses on supporting decisions for sustainable garbage collection route planning and optimisation. The objective is to create a practical solution for reducing CO_2 emissions and reduce negative impact on the environment as a result. From the design science perspective, a DSS is proposed, researched and developed to increase the effectiveness of municipal waste management. The paper also evaluates this approach against the Green IS framework.

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Pervasive computing; decision support system; sustainability; smart waste management

1. Introduction

Nowadays smart waste management is an integral part of Smart Cities (Schaffers et al., 2011; Anagnostopoulos et al., 2017). In October 2013, an article published by the (World Bank, 2013) states that 'By 2100,…, the growing global urban population will be producing three times as much waste as it does today'. This means that the need for an efficient waste management system is exceptionally high. For example, current practice of garbage collection in Melbourne, Australia (www.melbourne.vic.gov.au, 2017) requires the municipality to hire special workers, i.e. garbage truck drivers, for collecting garbage, and they still need to go through all the streets where the bins are located on a weekly basis, and receive the same salary regardless of the garbage bins in their area being full or partially empty. This creates extra cost to the municipality and produces additional air pollution as a result of unnecessary driving.

This research aims to improve environmental sustainability using sensor-based technology in waste management. The goal of the research is to facilitate information exchange between citizens, dispatchers of the garbage truck fleet and drivers themselves by employing modern sensor technology and information system infrastructure for decision support. This paper describes an innovative decision support system (DSS)

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architecture to support this process as an artefact of the design science research. This DSS is intended to aid a dispatcher in solving the optimal route problem for garbage collection based on the capacity and type of the trucks, and the start and end locations of the path. Using sensor technology, system collects all the notifications from the bins needed to be emptied, and shows them on the dispatcher's map, proposing the route to follow for garbage collection. We also consider a different type of vehicles designed to serve the needs of the citizens. Since the research goal is to find an optimal path for a particular truck, this is a modified heterogeneous vehicle routing problem (VRP), that is a modification of the classical VRP, which is capable to consider different garbage truck capacities.

2. Smart waste management approaches

We start by defining sustainable decision-making. as '… a decision-making which contributes to the transition to a sustainable society' (Hersh, 1999, p. 395). Sustainability issues usually represent a combination of three pillars: Economic, Social and Environmental (Gholami, Watson, Molla, Hasan, & Bjørn-Andersen, 2016), and the decision-making approach should be able to consider and integrate all three of them to some degree. These aspects might be lacking essential data, have multiple (sometimes controversial) goals, or have different stakeholders in charge and/or concern with achieving these goals. As much as it is difficult to distinguish the most important among three sustainability pillars, and thus the research presented in this paper focuses primarily on the economic perspective of sustainable decision-making, while at the same time combining it with environmental objectives (i.e. reducing carbon emission), and by doing so – contributes to the social benefits of the development of smart cities with smart infrastructure. The following subsection reviews the waste management process in smart cities to provide the background of how such complex objectives can be achieved.

2.1. *Smart waste management*

The smart waste management approach was introduced within the framework of Internet of Things (IoT) and smart cities. Zygiaris (2013, p. 218) defines 'smart city' as "… a certain intellectual ability that addresses several innovative socio-technical and socio-economic aspects of growth'. These aspects categorise smart city as 'green' referring to urban infrastructure for environment protection and reduction of CO_2 emission, 'interconnected' related to revolution of broadband economy, 'intelligent' declaring the capacity to produce added value information from the processing of city's real-time data from sensors and activators, whereas the terms 'innovating', 'knowledge' cities interchangeably refer to the city's ability to raise innovation based on knowledgeable and creative human capital".

Since this research is considered within the framework of smart city, we assume the usage of IoT technologies for the garbage collection optimisation, which assumes the usage of smart sensors for data collection. This technology becomes more and more popular, and since the beginning of 2000s there is a number of companies such as BigBelly (Bigbelly.com, 2003), Enevo (enevo.com, 2010), Compology (compology.com, 2012) that produce smart sensor solutions for smart waste management.

Morrissey and Browne (2004) reviewed the existing approaches for municipal waste management; and divided them into three categories: 'those based on cost-benefit analysis (CBA), those based on life cycle assessment (LCA), and those based on multicriteria decision-making (MCDM)' (p. 297). Based on the literature review, they argue that, the multicriteria methods are the most suitable for decision-making for waste management since they can solve any complex problem with several criteria, such as economic, social etc., while an LCA application is limited to an environmental focus.

The evaluation of effectiveness for different routing scenarios is one way of achieving environmental sustainability in smart cities. Traditionally, every model or simulation of smart waste management system considers the incinerator or the recycling facility as the end point of the route (Anagnostopoulos, Zaslavsky, & Medvedev, 2015). Usually, such facilities are located outside of the city, and the route from the last collected bin to the recycling factory is long and fuel-consuming. Anagnostopoulos et al. (2015) suggested an innovative approach to optimising vehicle routing by including in the model High Capacity Trucks (HCTs) and Low Capacity Trucks (LCTs). LCTs are meant to collect the garbage from the streets, and HCTs play the role of an intermediate storage unit inside the city. Consequently the LCTs do not have to go to the incinerator or recycling facility outside of the city, they can simply bring all the collected garbage to the HCT location and unload it, effectively reducing fuel consumption, and therefore reducing CO_2 emissions. The authors experimentally proved the efficiency of LCT and HCTs usage, therefore, for the research presented in this paper, we only consider scenarios with the usage of LCTs.

3. The design science research methodology for smart waste management

For the current project, we followed a design science research (DSR) process as proposed by Peffers, Tuunanen, Rothenberger, and Chatterjee (2007). The research design is depicted in Figure 1, and is adapted for the smart waste management DSS research in a PERCCOM (Erasmus Mundus PERCCOM, 2013) project context (the italic font in Figure 1 represents the current research project through the stages of DSR).

In a broad sense DSR is a type of research that – '… attempts to create things that serve human purposes. It is technology-oriented. Its products are assessed against criteria of value or utility – does it work? is it an improvement?' (March & Smith, 1995, p. 253). A DSS for Smart Waste Management is a complex system that requires a holistic approach and a model-based architecture. The system architecture links together different parts of the DSS, as well as the actors taking part in the current activity (see Figure 2). The core of the system is the optimisation model, which computes an optimal garbage collection route. The system supports short-term planning (in this case, the stakeholder is the coordinator of the truck drivers), and long-term planning, with the municipality as a stakeholder. It utilises the IoT data gathered from sensors to suggest the optimal route recommendations as the focus of the short-term DSS. The system can also collect these routes and other historical data over a period of time for statistical analyses, for example, on the frequency of emptying the bins in a particular area or the time of the day to simulate a 'what-if' analysis and for a long-term resource planning.

The following section describes the smart waste management mathematical model, and introduces the constraints and criteria used for problem-solving and optimisation.

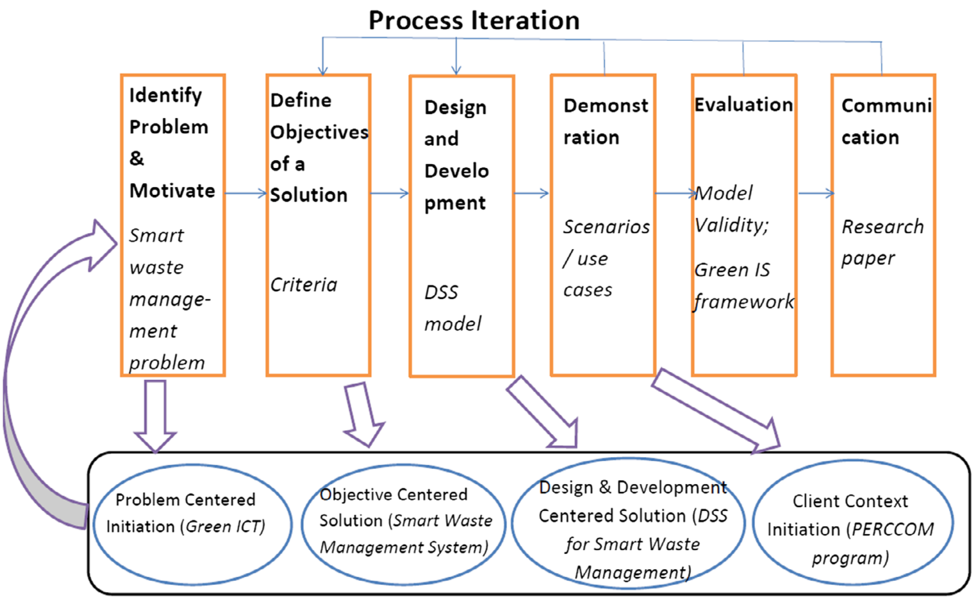

Figure 1. DSR Process iteration for smart waste management (adapted from Peffers et al., 2007).

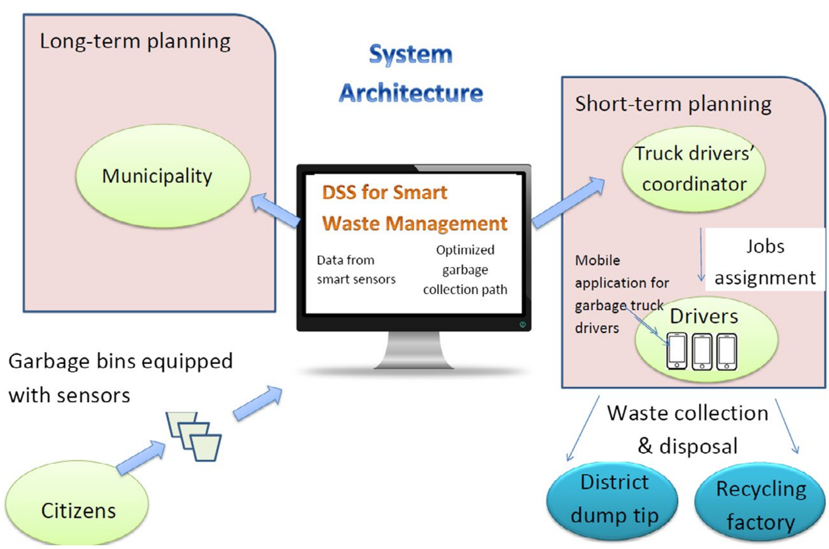

Figure 2. Smart waste management DSS architecture (adapted from Rybnytska, 2017).

4. Formal model implementation and simulation

A conceptual design and implementation of decision support solution for smart waste management involves formulating an optimisation model to describe value functions and constraints in running garbage collection in a city suburb when citizens are required to separate their garbage into three different kinds of waste – bio, plastic and other waste. This modelling is based on a particular practice in Melbourne, Australia garbage collection routine, but can easily be adapted to any other specific context – as long as people separate the waste they dispose into different waste categories, each of which is collected by the municipal services in a different way.

4.1. VRP for waste management as an extension of travelling salesman problem

The TSP remains one of the most common and well-studied problems in Operational Research. This problem was formulated by Applegate, Bixby, Chvatal, and Cook (2011, p. 1) as: 'Given a set of cities along with the cost of travel between each pair of them, the travelling salesman problem, or TSP for short, is to find the cheapest way of visiting all the cities and returning to the starting point'. The extension of TSP is VRP, which was discussed in a seminal work by Dantzig and Ramser (1959). The main goal is to minimise the routing costs. In our case, there are multiple pick-ups (emptying of garbage bins) and only one delivery (to the incinerator or big garbage collection truck).

Since VRP is an NP-hard problem, the most successful algorithms for finding the optimal route are heuristic algorithms. One of the most common approaches to VRP and its modifications is 'ruin and recreate' principle, when the chosen heuristic algorithm builds the solution, then some of the nodes are taken away from the solution, and then the other heuristic rebuilds a new solution by adding the excluded nodes (Schrimpf, Schneider, Stamm-Wilbrandt, & Dueck, 2000). Pisinger and Ropke (2007) developed an Adaptive Large Neighbourhood Search (ALNS).

The ALNS was implemented by GraphHopper Directions API with Route Optimization (2014) via JSPRIT toolkit. It provides APIs for routing and route optimisation, geocoding, map matching, matrix API and isochrone API. The company also developed an open-source java toolkit JSPRIT for solving TSP and VRP; and a java library for route optimisation. Based on the comparison by Medvedev, Fedchenkov, Zaslavsky, Anagnostopoulos, and Khoruzhnikov (2015) of different open-source tools and libraries for solving VRP, the open-source JSPRIT library was chosen for this research realisation.

4.2. Mathematical model formulation

We denote the number of compartments in the garbage truck $\boldsymbol{c} = 3$ (bio, recycle, other garbage). The path starts at the starting point $\boldsymbol{P}_0$ ($\boldsymbol{P}_0$ is different for each iteration), and ends at $\boldsymbol{P}_M$ – the location of HCT or incinerator. The mathematical model can be represented by the following system of equations and constraints:

$$\begin{cases} R = W \times f \times \sum\limits_{i=1,\, j=1}^{M} d_{ij}, \\ U = (B_i \times q_b + P_i \times q_p + O_i \times q_o) \leq V \\ \sum\limits_{i=1}^{M} \Delta_i \times (B_i + P_i + O_i) \leq V \end{cases},$$

where $\boldsymbol{N}$ – Number of houses/number of bio/recycle/other bins in the area; $\boldsymbol{V}$ – garbage truck volume of, m^3; $\boldsymbol{B}_i$, $\boldsymbol{P}_i$, and $\boldsymbol{O}_i$ – the amount of bio, plastic and other waste in the $\boldsymbol{i}$ – building, respectively, ($\boldsymbol{i} = \overline{1, \boldsymbol{N}}$); $\boldsymbol{q}_{b'}$, – numbers of full garbage bins of different types (bio, plastic, other respectively); $\boldsymbol{d}_{ij} = \boldsymbol{d}_{ji} (i = \overline{1, N}, j = \overline{1, N})$ – the distance $\boldsymbol{d}$ between the house $\boldsymbol{i}$ and house; $\boldsymbol{M}$ – total amount of nodes in the system ($\boldsymbol{M} \leq \boldsymbol{N}$); $\boldsymbol{f}$ – fuel consumption (litres/100 km); $\boldsymbol{W}$ – cost of 1 L of fuel, EUR; $\boldsymbol{R}$ – cost of collecting garbage, $\boldsymbol{R} \to min$; $\boldsymbol{U}$ – amount of collected garbage, $\boldsymbol{U} \to max$; Δ – the fill-level indicator (0 if not full, 1 if full).

We implemented this model for solving the heterogenioius VRP for smart waste management. The next section clarifies how the necessary secondary garbage volume data was obtained and calculated. In Section 5, the numerical results of the implementation of two different scenarios based on the current mathematical model are described and compared, as well as Scenario 3, where the vehicle does not take into account the information from smart sensors, serving all the garbage bins.

4.3. The secondary garbage volume data sources and calculations

As mentioned previously, Melbourne, Australia was used as a context for this project. According to the information from the Melbourne City Council (melbourne.vic.gov.au, 2015), the typical volume of the garbage bin is 120 or 240 L. Since the sensors determines the fullness of the bin, it was decided to schedule the pick-up when the garbage bin is 80–100% full, i.e. when the amount of garbage is in the range from 96 to 120 L and from 192 to 240 L. The Melbourne City Council provides the following information about the capacity of garbage trucks: the fleet consists of medium rigid vehicles, and the maximum load of such vehicles is 24 tonnes. However, for the research presented in this paper, we will consider the fleet of small rigid vehicles, and the load capacity of such type of vehicle is 4 tonnes.

To calculate the maximum load of the specialised LCT, we need to know the density of the particular type of garbage. We consider three types of waste: bio (food), recyclable (plastic, aluminium cans, cardboards, paper, glass), and all other garbage. The EPA provides the table with all the densities of different garbage types. To calculate the average density for the recycling waste, we will only consider the recyclable materials. To calculate the density of other waste we exclude recyclable and biodegradable waste.

Considering that the medium density of compacted bio waste is 1029 kg/m^3, recycling (excluding batteries and electronics) is 340 kg/m^3, and other garbage is 501 kg/m^3 (average value of all other types of garbage) (epa.vic.gov.au, 2017), it means that a specialised bio garbage truck can collect approximately 3887 L of garbage, a specialised plastic and cardboard collection truck – 11,765 L, other garbage – 7984 L. For further implementation, the volume of the 'bio' garbage bin is considered to be 4000 L, 'plastic' – 12,000 L, 'other' – 8000 L.

The idea of a new garbage truck type will be introduced now. So far, a truck with moving inner compartments doesn't exist (wasteadvantage.com, 2017); however, the moving compartment allows collecting different types of garbage, and in case one particular type of garbage prevails over others, to move the compartment to create additional space for the garbage of the prevailing type. The numerical results for this scenario and the comparison with the ordinary garbage truck type are performed in the next Section.

Table 1. The description of garbage bins' capacity and location.

N	Capacity	Location
('1')	(0, 98)	(22, 22)
…		
('150')	(0, 21)	(40, 94)

Table 2. The description of garbage trucks characteristics.

TruckID	Capacity	CostPerDistance	StartLocation	EndLocation
1_1	4000	1.1	(20, 20)	(100, 100)
1_2	4000	1.1	(20, 20)	(100, 100)
2_1	12,000	1.1	(40, 60)	(100, 100)
3_1	8000	1.1	(80, 60)	(100, 100)

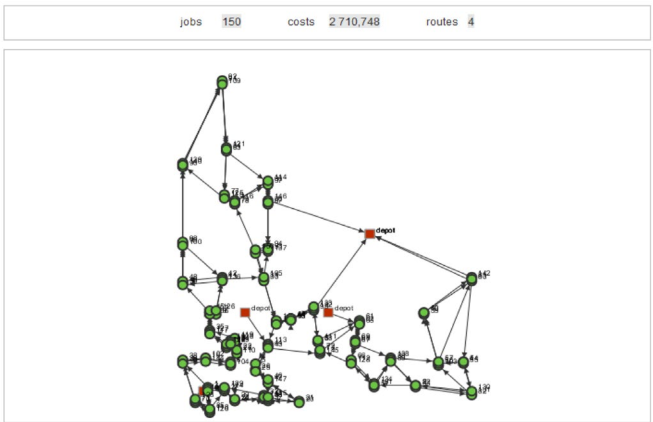

Figure 3. Scenario 1 execution results (adapted from Rybnytska, 2017).

5. Evaluation and discussion

5.1. Scenarios implementation

5.1.1. Scenario 1: without the usage of smart sensors

This scenario presents the current situation in waste management collection, i.e. only the typical specialised LCTs are considered (the garbage truck only collects the special type of garbage: either plastic, or bio, or other). We consider the number of garbage bins **N** = 150. The location of garbage bins is described in the Table 1.

Table 2 presents characteristics of the garbage truck. In addition, each garbage bin was tagged with 'bio', 'recycle' or 'other' label, to help the truck while collecting the particular type of garbage.

This scenario describes the current situation, when the garbage bins are not equipped with the smart sensors, and garbage truck drivers have to pass through all the bins without knowing whether they are full or not. The resulting paths are shown by Figure 3, while the numerical results of all three scenarios simulation are represented in Table 4.

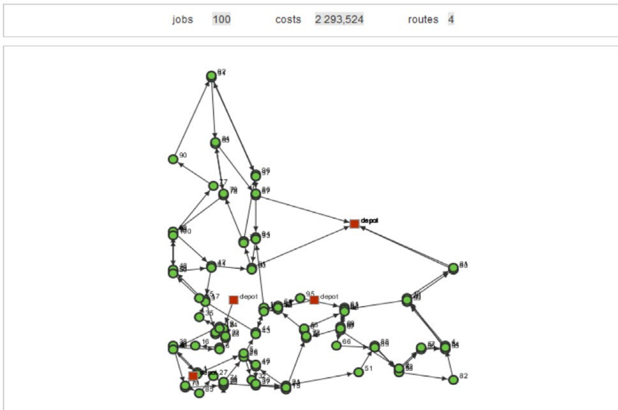

Figure 4. Scenario 2 execution results (adapted from Rybnytska, 2017).

Table 3. The description of garbage trucks characteristics.

TruckID	Capacity	CostPerDistance	StartLocation	EndLocation
1_1	8000	1.1	(20, 20)	(100, 100)
1_2	8000	1.1	(40, 60)	(100, 100)
1_3	8000	1.1	(80, 60)	(100, 100)

5.1.2. Scenario 2: specialised LCTs

This scenario considers the usage only of the special LCTs, with the data from the IoT sensors in the garbage bins now taken into account. In total, there are **N** = 100 bins needed to be emptied (see Figure 4 for simulation outcome). The locations of garbage bins are described in the Table 1 (however, only the 80–100% full bins are considered), while the characteristics of the garbage truck are also shown in the Table 2.

5.1.3. Scenario 3: unspecialised LCTs

The JSPRIT library implies penalties for each unassigned job (i.e. for each uncollected garbage bin), so experimentally it was discovered we need three LCTs with an average capacity of 8000 L to collect 100 full garbage bins. See Table 3 and Figure 5 below representing the initial conditions for running the scenario.

5.1.4. Results summary

As described, Figures 3–5 represent the results of the execution of all three scenarios, and these results are summarised in the Table 4 for comparison. We did not consider the scenario without smart sensors, but with the usage of unspecialised LCT because the usage of smart sensors has been proven to be more efficient for the smart waste management collection (Anagnostopoulos et al., 2015). For research purposes and the comparison of the CO_2 emissions for these scenarios, the distance metric is in kilometres. The average fuel consumption of the vehicle is 5 L/100 km; the average CO_2 emission is 2640 grams per litre diesel (ecoscore.be, 2017).

The third scenario considers the unspecialised LCTs, which means the truck can collect all types of garbage. In terms of CO_2 emissions, the 915 km long route produces around

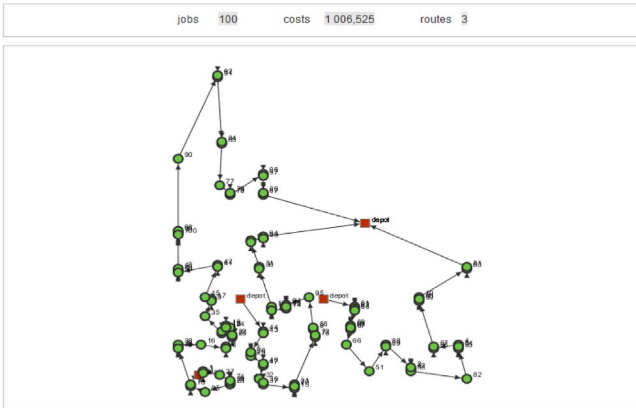

Figure 5. Scenario 3 execution results (adapted from Rybnytska, 2017).

Table 4. Numerical results of the scenarios' simulation.

Scenario	Truck ID	Capacity	Distance	Costs	Total distance, units	Total costs/ units	CO_2 emissions kg
Scenario 1	1_1	4000	391	430	2465	2711	325
	1_2	4000	458	503			
	2_1	12,000	810	891			
	3_1	8000	806	887			
Scenario 2	1_1	4000	325	358	2085	2294	275
	1_2	4000	356	391			
	2_1	12,000	705	776			
	2_2	8000	699	769			
Scenario 3	1_1	8000	422	464	915	1006	121
	2_1	8000	235	259			
	3_1	8000	258	283			

121 kg of CO_2. The second scenario, where only the LCTs are in use, takes 2085 km, and around 275 kg of CO_2 in terms of CO_2 emissions. It is clear that the third scenario is superior in terms of minimising CO_2 emission, producing less than half of the second scenario. Also, the third scenario uses only three garbage trucks with a total capacity of 24,000 L to collect every bin, while the same volume is not enough for the second scenario (4000 L of 'bio' truck capacity + 12,000 L of 'plastic' truck capacity + 8000 L of 'bio' truck capacity is equal to 24,000 L, but the same aggregated volume is not enough since each truck can collect only particular type of garbage. So, for the second scenario, the additional 'bio' garbage truck had to be added). Both these facts attest to the efficiency of the unspecialised LCTs usage, and the need of introducing this type of garbage truck to the market.

6. Conclusions and future work

The research presented in this paper focuses on the usage of DSS for Sustainable Development. Gholami et al. (2016) highlighted the lack of practical 'impact-oriented' solutions for the ill-structured questions of Green ICT and Sustainability, and the current project aims to fulfil this gap. As the example use case, the smart waste management case was chosen. The idea of the project was to create a decision support tool for the coordinators that allows the drivers of the garbage trucks to choose the optimal path for collecting garbage. It was also shown with the help of different scenarios that the modern way of garbage collection requires new and innovative solutions, and modifications to the garbage truck was suggested to improve the garbage collection process. By introducing such modifications, we have received more than a 50% reduction in both distance covered and CO_2 emission.

The project has a potential for further research. First, the impact of the city size is an opportunity for future investigation. Secondly, the data collected from sensors and then processed by the DSS, can be used by the municipality for the prediction of the garbage bins fill trends. It is obvious that, for example, during the weekend garbage to a higher extent is generated in residential neighbourhoods than on weekdays, and, therefore, they might require their garbage bin to be emptied sooner. At the same time, there's an opportunity to use the data from DSS as the foundation one for deciding where to build an incinerator and of which type. For example, offices in the city centre usually don't produce much bio waste, whereas the amount of paper and plastic waste may be significant. It might be reasonable to have the incinerator for plastic and paper somewhere not far from the office part of the city, to reduce the distance HCTs would need to cover to bring the garbage to the incinerator.

Also, the emerging trend of blockchains might be connected with the current research. When citizens are ready to bring their garbage to the garbage bin, they can just notify the system using mobile application, and pay a certain amount of money via a mobile application. The driver of the LCT comes to pick up the garbage, and when he collected all the garbage at the locations proposed by DSS, again a certain amount of money will be transferred to his account. All the payments might be made using blockchains as a modern and safe way to transfer and receive money.

Disclosure statement

No potential conflict of interest was reported by the authors.

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