Asian Journal of Applied Science and Technology (AJAST)
(Open Access Quarterly International Journal) Volume 2, Issue 2, Pages 387-394, April-June 2018

IOT Based Waste Management in Smart City

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Article Received: 29 January 2018 *Article Accepted: 26 February 2018* *Article Published: 17 April 2018*

ABSTRACT

The Internet of Things (IoT), as expected infrastructure for envisioned concept of Smart City, brings new possibilities for the city management. IoT vision introduces promising and economical solutions for massive data collection and its analysis which can be applied in many domains and so make them operating more efficiently. In this paper, we are discussing one of the most challenging issues municipal waste-collection within the Smart City. To optimize the logistic procedure of waste collection, we use own genetic algorithm implementation. The presented solution provides calculation of more efficient garbage-truck routes. As an output, we provide a set of simulations focused on mentioned area. All our algorithms are implemented within the integrated simulation framework which is developed as an open source solution with respect to future modifications.

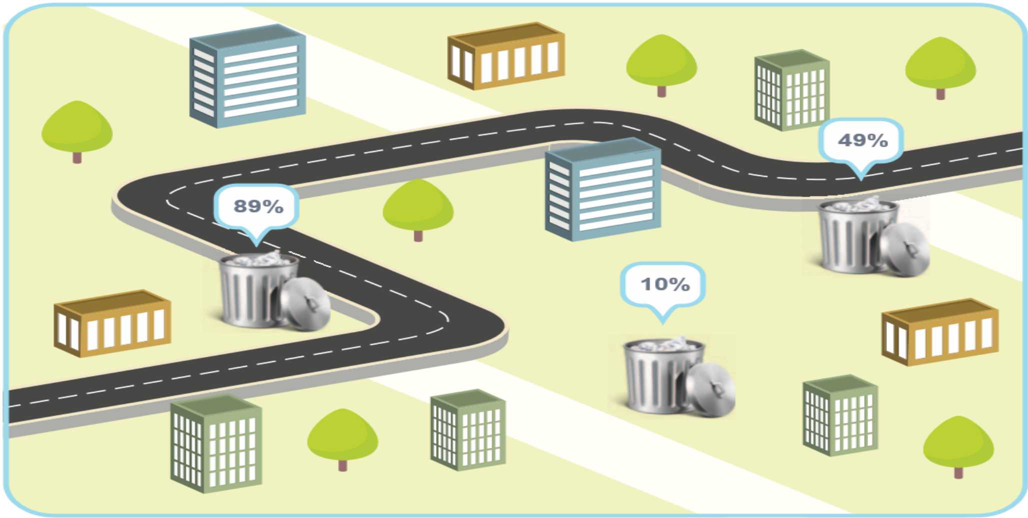
Keywords: Environment, waste management, environmental pollution, recycling, ecology, natural resources and ecosystems.

1. INTRODUCTION

The Smart City represents nowadays hot topic in terms of improving living conditions. Considering mainly the situation in European Union, the EU national governments and also private companies are investing every year significant amount of their budgets to research, development and implementation of the concept of Smart City. Therefore, the term Smart City has many different ways how to define it. In current research, this term is considered as question of How to improve a city on different levels?. Those levels could be related to different stakeholders (i.e. government, authorities, private companies, citizens, etc.) and/or various fields (i.e. mobility, open data, energy efficiency & low carbon solutions, policy & regulation, waste management). The data analysis is a common base-ground for above mentioned issues of the Smart City concept. The Internet of Things (IoT) is currently considered as a basic communication infrastructure for smart cities, where machines communicate automatically between each other (Machine-to-Machine, M2M) [1]. The biggest advantage is the cooperation of many different communication technologies and devices (machines) within one functional system, where big amount of information and data are shared and used in a secure and smart way. With the Low-Power Wide Area Network (LPWAN), see Fig. 1, IoT idea comes closer to the real implementation.

The LPWAN technologies bring low-cost (1$ yearly per spot) and low-power (50μW for connection hub / modem) solutions for million-spot connectivity of various devices, Our work focuses on the optimization algorithms for Smart City management and more specifically this paper deals with municipal waste collection procedure. We consider existing IoT infrastructure and sensor networks, already deployed i.e. in France, where the communication is based on Sig Fox technology [5]. It should be connected to the main infrastructure built in the city. That they can provide the valuable information set for the waste management. In Fig. 2, we can see an example of such considered scenario This network could use the LPWAN technologies such Sig Fox, LoRa WAN, Weightless, Link Labs, Nwave or different technologies which create low-power and low-cost communication infrastructure [13]. Currently, the main issue regarding waste collection is that the garbage-trucks are operated ineffectively. The cities contain different and various areas, where some bins need to be picked-up more often than others.

When we consider installed bins as points without actual information (i.e. about the bin weight), we will lose time, money and also the trucks, which could be used in different places. The sensor network and IoT infrastructure represents a tool for extracting the information from the bins. Further, obtained data might be used for truck-road calculation and optimization and also for analytical statistics of bin loading (i.e. if the bin will not be overloaded till next collection).

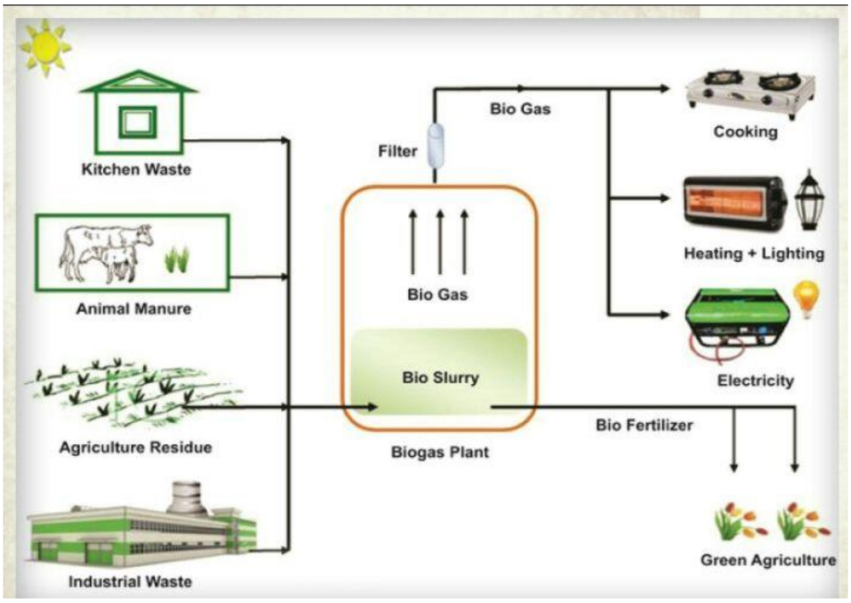


Insufficient. efficiency in some more difficult cases of waste collection. The large amount of variables was the reason for large computation time. The recent research works [22]–[24] use mostly the heuristic solutions and methods dealing with the municipal waste collection as with a Travelling Salesman Problem (TSP). Dealing with problem formulation, the effectiveness of optimization and computation is based on input parameters and specific problem implementation.

Only few works tried to use evolutionary algorithm to deal with implementation and optimization of waste collection problem as the TSP defines. These works, use Ant Colony algorithm. However, the genetic algorithm was also proven as a very effective tool to deal with TSP of various implementations, but not in the specific implementation of waste collection. We provide in this article experimental measurements focused on the usability of genetic algorithm in the real implementation of the municipal waste collection problem.

Anaerobic Digestion

Anaerobic digestion occurs naturally, in the absence of oxygen, as bacteria break down organic materials and produce biogas. The process reduces the amount of material and produces biogas, which can be used as an energy source. This technology is commonly used throughout the United States to break down sewage sludge at wastewater treatment facilities. In the past few years, there has been a movement to start adding food waste to anaerobic digesters already in place at wastewater treatment.

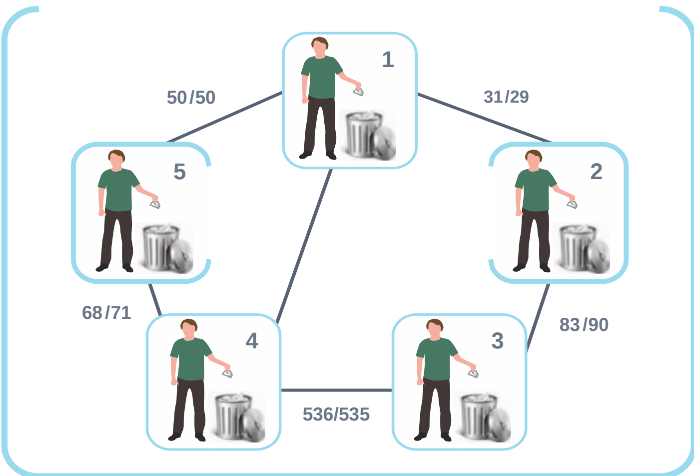


The anaerobic digestion of food waste has many benefits, including:

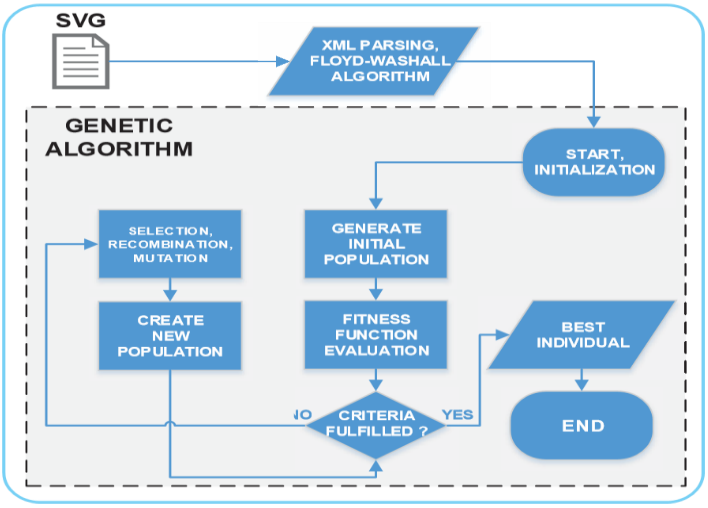
Climate Change Mitigation – Food waste in landfills generates methane, a potent greenhouse gas. Diverting food waste from landfills to wastewater treatment facilities allows for the capture of the methane, which can be used as an energy source. In addition to decreased methane emissions at landfills, there are greenhouse gas emissions reductions due to the energy offsets provided by using an on-site, renewable source of energy.

Economic Benefits – Wastewater treatment facilities can expect to see cost savings from incorporating food waste into anaerobic digesters. These include reduced energy costs due to production of on-site power and tipping fee for accepting the food waste.

Diversion Opportunities – Most municipalities are investing in ways to divert materials from landfills. This is usually due to reduced landfill space and/or recycling goals. Wastewater treatment facilities offer the opportunity to divert large amounts of food waste, one of the largest waste streams still going to landfills.



If needed, one-way road might be done with infinite value of the weight parameter. The weight is computed as a sum of all parameters which impact the road (i.e. distance, traffic-density, road quality). The weight of road could be also used as a index of expenses for the road (longer road with high traffic-density will be more expensive than shorter road with fluent traffic). The SVG file consists the basic parameters and attributes for graph creation (i.e. ID of vertex - where it begins and ends, final number of vertices). The basic schematic of our algorithm is introduced.



Description of used genetic algorithm

Our implementation of genetic algorithm is divided into the following basic parts:

- Representation and generation process for population.
- Optimization process of selection, recombination (crossover) and mutation.

Main criteria for choosing best individual and best solution

The initial population is given by final number of nodes and first road. The first road is randomly generated. This is also the input parameter for the fitness function. When we have the initial population, the main process of optimization starts.

The selection goes first – we use the truncation selection. It retains the fittest x% of the population. These fittest individuals are duplicated so the population size is maintained. This type of selection has then only one parameter τ, $\tau \in (0,1)$, which gives $\tau \cdot N$ best individuals from the old population.

Next step is the crossover and mutation. The crossover is given by a maximum limit of crossing (which is also the minimum value of mutation). From this value the ratio of crossing and mutation is also coming. The dynamical value of crossing given by maximum crossing value is chosen because the same roads can occur in the new population. The same individuals should not be crossed, but mutated to get better or new individual.

The mutated new individual p_m is again defined by group of nodes (road) and road weight. The final end parameter for the whole process of the optimization is given by minimum weight change of road over defined time (iterations).

This means that if the new solution is not better in α iterations compared with old solution more than β %, the program will end. This algorithm condition secures the against stacking in local maximum or minimum.

2. RESULT AND CONCLUSION

SIMULATION AND EXPERIMENTAL PRE-SETS

The simulations and our measurements were done on the machine with following configuration: processor Core 2 Duo E8200 on 2.66GHz, 4GB RAM on 800MHz and 64-bit system. The initial parameters, which are changing in the course of the measurement method, are following: population size 5000, max. crossing 40%, selection 60% (throwing 40%) and 80 vertices.

Population Size Impact: The size of population impacts the power requirement, time requirement of the algorithm, but also influences the success rate of finding best solution. This chapter provides measurements analysis regarding the best settings for the population as shown, improvement of road weight is more than 25%, but we need to consider the time: iteration ratio, which exponentially decreases to zero. Around 50 population we achieve 12.5% of road weight improvement and only 40% speed decreased. This means that we achieve 50% of possible improvement with less than 50% speed decrease. This represents important output, because when the GA will be implemented in the low-power devices, it is necessary to deal precisely with algorithm efficiency and time demands. Smaller effective population (in our case 50 population) should be chosen for low-power solution and if we have *no-power-constraint* implementation then the biggest possible

Population Throwing Impact: The throwing process is connected with selection. We select the best individuals and throw the others for generating new individuals from mutation and crossing. The results of measured throwing impact are provided in Tab. II.

The computation time is oscillating between 60 to 80 seconds. But the time: iteration ratio is decreasing. The interdependency of population throwing, weight and *time: iteration* ratio is displayed in Fig. 7.

Further, we can see the. That till 40% is worth to throw the old population, because it has positive impact on the road weight. More than 40% of throwing has negative impact on the road weight with also continuously growing time requirements for one iteration.

Crossing and Mutation Ratio Impact: The crossing and mutation are the main methods for optimization in our used genetic algorithm. The crossing creates bigger changes in the new population or individual and it has potential to find better solution as it was found previously. The mutation is doing only small changes with exchanging two nodes and it also helps to the algorithm not to stuck in local minimum or maximum. Then the crossover takes place at the beginning of the optimization process and the mutation at its end. Mutation has also less power requirements and it is possible to handle more mutations in one time unit as crossovers. The main results of measurement of *crossover: Mutation ratio impacts are* displayed in Table: 1 Weight with Time

Crossover	Weight span	ø Weight	ø Time [s]	Iterations
0 %	2820–3115	2960	44	1057
10 %	2580–3140	2840	46	574
20 %	2600–2945	2740	54	443
30 %	2560–3050	2750	63	411
40 %	2545–2960	2730	77	381
50 %	2470–3025	2720	92	418
60 %	2440–3020	2740	117	493
70 %	2510–3040	2750	124	425
80 %	2540–2955	2760	129	356
90 %	2665–2875	2770	122	306
100 %	2775–2970	2850	125	216

Costs saving in the Waste Collection

These measurements compare three different scenarios with 40, 60 and 80 nodes (vertices). With this model, we can estimate the cost saving for one cycle of waste collection. The Tab. IV shows that the average improvement is about 15% (from 9.52% to 20.66%, if we look to the min., max. and average road weight). If we consider the existing IoT infrastructure, the 15% costs saving is worthy and it is general cost saving for one travelled km by the garbage truck. These resources might be invested i.e. to spread the garbage trucks into the bigger area or more often waste collection.

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Vertices	Weight span	ø Weight	ø Time [s]	Iterations
80	2480–2960	2640	63	672
60	2220–2530	2310	33	305
40	1960–2365	2050	24	162

The article introduced the upcoming IoT infrastructure for smart cities and putted it in the context of municipal waste management. We provided the summary on municipal waste collection management methods and showed the examples of solutions introduced by recent research in this area. Given overview showed that it is not yet enough discussed the possibility of using genetic algorithms as a optimization method for waste collection. Our solution is based on the idea of IoT infrastructure, which should provide enough information to handle this Smart City issue more efficiently. The main part of the article provided experimental measurements and results, which proved the power of GA and also the possible cost savings (in average 15%). The best parameters for the GA settings were shown (40% throwing, 20% max. crossover, population based on power requirements), when the low-power and power independent real implementations were also considered.

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