Multi-objective Decision-Making Framework for Effective Waste Collection in Smart Cities

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Abstract – Metropolitan cities often experience waste collection challenges due to ineffective methods of collection. This paper described criteria and an approach for efficient decision-making for waste collection that will make use of data generated by IoT-enabled objects. This implies taking into account multi-objective goals in the collection process while dealing with complexities such as data loss during IoT based data collection. Understanding current decision-making algorithms highlights the deeper insight required for IoT based decision-making algorithms. There is a need for decision-making algorithms to be dynamic so that they can address different levels of data loss inherent in IoT data collection. This paper presents the criteria to be considered and a model for smarter decisions in the smart city as applied to waste collection.

Index Terms – multi-objectives; decision-making; Internet of Things; waste collection

I. INTRODUCTION

A Smart City is an Internet of Things enabled data-driven platform that utilizes digital data collected from interconnected and Internet connected devices in the city [8] [9]. The increase in the number of interconnected devices is taking the complexity of data to higher level [10]. The data that is generated by these devices is real time and can contribute to obtaining insights to improve services such as traffic, transportation, management of resources and services. The challenge is making sense of this data (smarter decisions) while it is still in motion [11][12].

Figure 1: Ineffective waste collection methods

According to the Joburg 2040 [13] growth and development strategy, one of the aspects to be addressed includes 100 percent waste collection through appropriate recycling and waste reduction approaches. A need exists to enhance waste collection effectiveness as to mitigate the scenario as presented in Figure 1.

The waste collection challenge brings about an opportunity to propose algorithm(s) that can enhance the smarter decisions in a Smart City. The algorithm needs intelligence. The objective for this paper is to analyze and propose models for a decision-making algorithm that will be sufficiently dynamic to address different levels of data loss.

II. BACKGROUND

IoT generated data has specific characteristics (has a high volume, is received with a high velocity – is in motion, is of different varieties, and might have missing data observations). The following elaborates on these characteristics:

Data volume – the more data you receive, the harder it becomes for traditional ICT infrastructure to handle. The decision-making becomes a challenge for the ever-growing heterogeneous data, easily running to terabytes or even petabytes of information [19][20].

Data velocity – the faster the incoming data, the bigger the challenge to process data within an adequate response time [21].

Data variety – data comes from various sources and thus it is challenging to process into a form where insight to the end user can be extracted [22]. The accuracy of decision-making can be impacted when data is poorly processed.

Missing data – refers to incomplete data that may lead to inconsistent decisions [23]. Factors such as poor network connectivity or sensors generating data in parallel can lead to data loss. Missing data needs to be addressed when sampling data for decision-making. This work focuses on missing data.

III. LITERATURE

There are existing approaches that have been used to address the waste collection. These algorithms are typically not Internet of Things (IoT) based i.e some do not use streaming data and some do not make real-time decisions. IoT represents views towards a dynamic and self-configuring global network infrastructure that is standards-based and supported by interoperable communication protocols that use intelligent interfaces, and are seamlessly integrated into the information network [18]. An advantage of using IoT is that the solution will be well-instrumented, well-connected and will enable real-time decisions.

Table 1 describes general criteria to be considered for waste collection in a smart context. These criteria include if the data is in motion, if multiple objectives are addressed, if data can be lost and if there is significant data volumes. The algorithms are evaluated against these criteria. The paragraphs below provide high level descriptions of the algorithms considered as well as an overview of the criteria used.

Genetic algorithm [5] – approaches waste collection by identifying where similar composition of waste constituents are generated and the impact it has towards the socio-economy. Buenrostro-Delgado *et al.* [5] believe that the results may be useful to decrease cost and to improve collection services. Data was analysed using descriptive statistics and multivariate analysis. However, this genetic algorithm becomes slower when dealing with fast increasing data and it does not address the issue of missing data.

Backtracking search algorithm [3] – introduces a threshold to the waste level by using capacitated vehicles. Even though this approach uses streaming data it does not address the issue of missing data.

ArcGIS [7] – is a convenience for decision makers to choose appropriate planning solutions that make great benefits of socio-economic strategies. This approach addresses travelled distance, trips and collection time using data at rest.

Heuristic [4][6] – the aim of this approach is to reduce high collection and transportation cost. It addresses three phases of route (from household, to the collection centre, to the transfer station, to recycling centre, to the landfill). It was evaluated against general purpose mathematical programming software package and decision rules.

Particle Swarm Optimization [7] –this approach takes cognisance of vehicle capacity and shifts constraints. Its primary aim is to maximize collected waste quantity.

The following criteria were used to evaluate the above algorithms against the need of a smarter IoT enabled decision-making algorithm.

Data in motion - the continuous generation of data from the devices is referred to as data streaming [15] and typically has different challenges and characteristics from data at rest (e.g. contained in a database) [14]. One of the challenges refers to a case where the data stream contains erroneous information [14]. In any business, the quality of data will have a ripple effect. The effect of missing data, and inaccurate and meaningless information may negatively affect companies. Quite often organizations struggle with the accuracy of data underpinning day-to-day decisions [16]. It is important to address the data in motion challenges, given that data observations might be lost in decision-making algorithms.

Multi-objective - The smart decision-making must be independent of prior bias. The only components that must be considered are the patterns that will indicate the data behavior. Multi-objective formulations are realistic models for complex engineering optimization challenges. In real life, objectives under consideration may conflict with each other. Optimizing a solution with respect to a single objective can result in unacceptable results with respect to the other objectives [17]. One example is determining an optimal route, which considers time and the fuel cost (e.g. it might a route might use less fuel, but will take longer to travel).

Table 1: Comparison of waste collection approaches

Algorithm(s)	Data in motion	Multi-objectives	Data loss	Data increase
Genetic algorithm [5]	X	Single	X	X
Backtracking search algorithm[3]	√	Sequential	X	X
ArcGIS [7]	X	Single/ Sequential	X	√
Heuristic [4][6]	√	Sequential	X	√
Particle Swarm Optimization [7]	√	Single	X	√
Expected algorithm (s)	√	Simultaneo us	√	√

It may be a critical case to choose which objective to prioritize. Multi-objective optimization algorithms can identify solutions in the Pareto optimal set [17]. Pareto optimal is the type of multi-objective decision-making that compromises at least one objective. Table 1 indicates that none of the approaches address multiple objectives simultaneously. The desired decision-making algorithm is expected to address multiple objectives simultaneously.

The use-case suggests that more than one objective will need to be considered simultaneously. Multi-objectives have been applied in many real-life problems where objectives under consideration conflict with each other [17]. The waste collection objectives would be to reduce pollution when bins are collected on time, find an optimal route that will save time and fuel while choosing the appropriate truck size. This paper proposes a model that can be used to build an algorithm which can operate in multi-objectives and multi-disciplinary IoT environments for smart waste collection.

Data loss - refers to the incomplete data that may lead to inconsistent decision-making [11]. Factors such as a poor network, faulty sensors, etc. Missing data needs to be addressed when sampling data for decision-making. Table 1 shows that the existing approaches have not addressed missing data in waste collection. A decision-making algorithm should be able to make decisions knowing that there is missing data. Knowing the total number of bins makes it easier to calculate the percentage of missing data. The percentage of missing data needs to be considered in the optimization algorithm.

Increased data - the greater data volume, the harder it becomes for the traditional ICT infrastructure to handle. The decision-making becomes a challenge for ever-growing data of all types, easily gathering terabytes even petabyte of data [1]. Various visualization and decision-making methods have been proposed previously, but the only consistently popular one is the one that can handle two or three objectives. However, this algorithm cannot be extended to handle more than 3 objectives due to fast growing heterogeneous data [2]. Table 1 shows that some algorithms are able to handle fast increasing data. The genetic algorithm [15], for example, becomes slower when handling fast increasing data. An expected algorithm should be able to handle Internet of Things data, make a real-time informed waste collection decision and be able to validate data (i.e. is the data sufficiently complete to make a reliable decision).

The waste collection algorithms analysed were implemented to yield effective methods of waste collection. However, the theoretical evaluation indicated that not all of the algorithms used data in motion, addressed objectives simultaneously, can handle fast increasing data and none of them addressed the issue of data loss.

A. Algorithm considerations

Use case scenario: *There are bins that need to be collected in an area. The number of bins suggests which truck to be used. The truck must use an optimal route in order to save time and fuel (cost). An area is considered to be less polluted if bins are collected on time.*

An algorithm must address the following objectives:

- Reduce pollution (bins are collected on time).
- Improve cost efficiency (truck size and reduced fuel consumption).
- Use the optimal route (prioritize time and cost).

The proposed algorithms should be dynamic enough to learn and adjust to the following data factors:

- High velocity of incoming data leads to high volume of data to be processed per decision.
- High volume of incoming data can make the decision-making algorithm slow or even crash the algorithm.
- Data generated in similar sensors at the same time comes in parallel and it is possible for one entry to be lost during communication. Data loss can lead to poor decision making.

IV. PROPOSED MODEL

A model is proposed below to guide the implementation of smart decisions for waste collection. This model should be able to parameterize objectives, analyses the scenario, select a weighted co-efficient based on the analysis and make decisions. Figure 2 shows the proposed decision-making model.

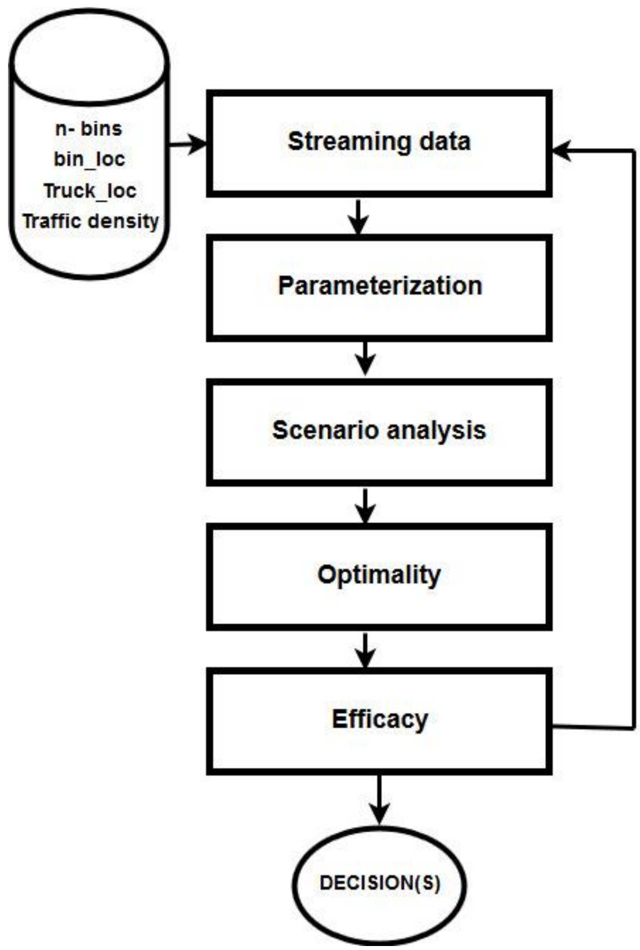

Figure 2: Waste collection decision-making model

The following questions are raised based on the proposed model: What kind of data used (streaming data)? What are the parameters (parameterization)? Which objectives to prioritize or what are the crucial objectives and how much is data lost (scenario analysis)? Will the model help us to collect all bins on "time"? Whereon "time" is less than 24/48 hours after indications that bins are full and also help to save fuel cost and select a right truck size (optimality). In case of conflicting objectives, were the objectives achieved without compromising the other (efficacy)? Then implement the decisions.

Given these components, the selection criteria is required (optimality) in terms of which of these components need to be prioritized without compromising their impact on the final model output. The travelling salesman problem algorithm helps to get an optimal route (shortest distance and minimum time) and is an NP-hard problem in combinatorial optimization. However, the probability is low to discover a theory or an approach that allows one to 'optimize' two objectives equally without the other one being compromised and address data loss at the same time.
The following provides more detail for each of the components in the proposed model.

A. Streaming data

The collection process of data at rest and data in motion is similar; the only difference is the analytics. The analytics for the data in motion happens at real-time as the event is taking place.

B. Parameterization

This component establishes a relationship between the problem variables (i.e. route, time and fuel consumption) the data received and objectives as part of decision-making goal. This phase helps to define fuel consumption per distance, get total distance between a nearest truck and all bins that need to be collected.

C. Scenario analysis

This component analyses the scenario by indicating which objective to prioritize between time and the cost. The selection weighting co-efficient based on the scenario suggests which objective to prioritize. Possible cases are as follows:

Cases:
The scenario builds four possible cases, those cases are as follows:

- **Case 1**: Too many bins + light traffic → Priority is TIME
- **Case 2**: Fewer bins + heavy traffic → Priority is COST
- **Case 3:** Fewer bins + light traffic → ANY
- **Case 4**: Too many bins + heavy traffic → COST and TIME

D. Optimality

The goal is to extract useful information from the sensing of bin and truck locations. Typically, the data contains information about location and status of the bin and/or the truck. This component addresses the issue of multi-objective optimization. The objectives (time and cost) are equally crucial, however, there is a need to enumerate implication of each scenario to fit it in a bigger picture of optimization. In this case, it is 'time' versus 'cost-effectiveness'. The multi-objective problem is defined as:

Combined objectives of cost and time: Minimizing cost, minimizing time and include a percentage of a missing data.

Subject to: the calculated total distance (route) to be travelled per trip. Trip includes moving from truck’s current location, to the city and to the dumping site.

Then: Calculate cost (in rands) per trip. Knowing truck consumption per kilometre and fuel rate, will help to calculate the total cost per trip.

Then: Calculate the total time for collection. The total time will depend on distance and traffic density.

The combined or simultaneous objective is a joint minimization of collection time and collection cost. For simplicity, the collection cost here is modelled as the total fuel cost. Other associated costs can be included in the model without loss of generality. Constraints specify that distance (route) between truck and bin is equal in both directions. The constraint of limited resources sets a maximum threshold on the collection cost. Similarly, a threshold on collection time is ensured. However, other constraints such as labour time, capacity and cost indicate that only a single truck is allowed to pick a bin and that bins along the same route are collected by the same truck.

Weighted sum

Considering the priority cases in Section C, the problem of combining cost and time objectives can be formulated into a single objective problem via the weighted sum method, thus:

$$Aw = \alpha \Delta c Ac + (1-\alpha)\Delta t \mathrm{At}$$

Where “α” is the weighting factor and $0 \leq \alpha \leq 1$; “A” denotes average, “c” denotes cost, t” denotes time and “w” denotes weight.

The value of α is selected based on priorities for the two objectives (i.e cost and time).

E. Efficacy and decisions

This component suggests which truck to take, which route to take and conduct some evaluation metrics as to how much time and cost it will take per collection trip. The algorithm will repeat the process as shown in Figure 2 after a certain period that needs to be identified when the algorithm is tested.

IV. CONCLUSION

This paper presented a model to guide the development of smart decision-making algorithms for application in smart city waste collection environment. A multi-objective optimization model (with collection time and cost as objectives) for the waste collection use-case is developed and the weighted sum method suggested for converting the model into a single objective model based on known priorities. Intelligence to measure the amount of data loss and decide which objective to prioritize based on scenario analysis is required. Knowing the nature of a scenario (using data) helps to know which objective is crucial for decision-making. The environment will stream data from bin sensors, send it to a platform, and the platform will do decision-making. Furthermore, the decisions will be evaluated using an error function. It is believed that implementations following this model can be used for smarter decision-making which ultimately can improve waste collection in cities.

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