IoT-Enabled Smart City Waste Management using Machine Learning Analytics

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***Abstract*—Waste collection and management presents a major challenge for municipalities wanting to achieve cleaner urban environments. Smart city infrastructure incorporating the Internet of Things (IoT) paradigm offers substantial advantages in terms of real-time waste monitoring capability. Basic sensory monitoring by itself, however, falls short of achieving optimal waste management without comprehensive data analytics. To this end, the present work proposes an off-the-shelf IoT-based waste monitoring solution, combined with back-end data analytics for efficient waste collection. The work employs Raspberry Pi and ultrasonic sensors, mounted on waste-bins in a specific area of a cooperating municipality for waste capacity monitoring. Real-time bin status and machine learning analytics are used to identify present as well as predict future waste collection scheduling. Dynamic collection servicing routes are accordingly mapped for utilization by waste collection vehicles. During a ten-day trial and validation period, it was observed that the proposed design increases fuel efficiency by up to 46% and a reduction in collection times by up to 18%. In addition to the noted quantitative improvements, the proposed scheme can also aid in optimizing long-term waste policies in smart city environments using the recorded statistics.**

Keywords—Internet of Things, Smart City, Machine Learning, Optimization Theory

I. Introduction

Efficient waste management in urban environments including towns and cities is an ever-increasing challenge. Manual waste collection mechanisms following fixed schedules, routes and collection points fails to fully address urban waste collection requirements, changing waste generation patterns and define efficient provisioning of resources to maintain a cleaner environment [1][2]. The emergence of the Internet of Things (IoT) paradigm provides administrators a useful tool to optimize waste collection using intelligent monitoring and analytic solutions furthering the realization of truly *smart* cities [3]. An increasing number of prior studies have therefore, started investigating the utilization of IoT in urban areas for improvement in infrastructure monitoring leading to accurate and real-time resource provisioning, especially focusing on garbage collection and management [1-7]. IoT sensors in essence however, only provide monitoring capability. In addition to recording and storage of sensory information, the recorded data needs to be analysed in automated and intelligent manner for real-time resource allocation as well as in defining long-term policies from a management perspective. While prior work in this area has resulted in solutions focusing on particular aspects of the waste collection process, from addressing collection fleet breakdowns to monitoring compliance of collection teams, further work is still needed to devise a comprehensive and scalable solution for wider deployment. The present work seeks to further the implementation of IoT technology for waste collection in urban environments using sensory monitoring and intelligent back-end processing facilitated by machine learning to monitor as well as predict the status of residential garbage bins. Using off-the-shelf bin-mountable hardware, a monolithic solution is proposed to monitor as well as dynamically schedule bin-servicing. Additionally, supervised machine learning is used to predict anticipated bin capacity over future time-bins to economize the collection cost and increase operational efficiency. The system has been trial-tested in an urban area of a cooperating municipality to benchmark the efficacy of the proposed approach and study results from a quantitative as well as qualitative perspective.

The rest of this paper is organized as follows. Section II presents a background on the use of IoT in waste management including the off-shelf components employed and related work in the domain. Section III highlights the proposed design, the primary components of the system and the waste management routing algorithm. Section IV evaluates the design in a practical setting along with a discussion of quantitative and qualitative results. Final conclusions are drawn in section V.

II. Background

A. IoT & Data Analytics: Hardware and Software Utilities

Increasing interest in use of IoT for monitoring and management purposes has spawned a number of off-shelf hardware and software utilities for IoT system development. Among the growing category of devices in this domain, Raspberry Pi is quite popular in experimental deployments. Standard Raspberry Pi can be categorised as a complete computing solution, hosting a general purpose Linux or Microsoft Windows based operating system (depending on deployment scenario) as well as an application development environment. Due to ubiquity of use, the present work employed Raspberry Pi version 3 and ultrasonic sensors, as detailed later in section III. Application development was

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carried out in Python using machine learning (prediction) libraries of the standard C5.0 decision tree algorithm [10].

B. Related Work

As highlighted earlier, monitoring and management of waste collection facilities in urban environments is increasingly being considered as an avenue of investigation using IoT paradigm. IoT sensors, in addition to providing real-time status of waste-bin capacity may also facilitate useful data analytics to economize waste collection process. Overall the deployment of IoT technology for waste collection however, is relatively nascent with ongoing work in several underlying avenues to realize a practical and scalable solution. The term 'Internet of Bins' for example, coined by Keerthana et al. in [1] describes IoT-enabled smart trash management employing sensors, microcontrollers and a software utility to monitor and service garbage bins. The proposed system allows automated locking of bins exceeding capacity to avoid waste over flows [1]. Kumar et al. [2] discuss a similar intelligent IoT based smart garbage alert system, using a basic threshold to alert municipality and request cleaning. RFID tagging at the bins as well as collection trucks is used to validate cleaning team compliance to requested scheduling. On a slightly different strand, Anagnostopoulos et al. [3] highlight the requirement of robustness in waste collection process, using dynamic routing of vehicles to address collection fleet breakdowns resulting in lower costs over manual routing. Although basic threshold monitoring to schedule bin collection is a step up from relying on static waste collection timelines, adding further real-time intelligence to further economize the process is a fundamental requirement. Dynamic scheduling of vehicle routes using *–k* query algorithm was therefore, proposed in [4]. The scheduling algorithm worked on the principle of locating the first available collection truck that could load waste from *k* bins using Google Maps integration to facilitate drivers. Shayam et al. [5] on the other hand, utilized IoT-based waste monitoring to forecast bin status, pursuing further optimization of the waste collection process. Using genetic algorithms, Fujdiak et al. [6] detail the optimized selection of garbage bins to be serviced, and highlighted up to 15% improvement in waste collection costs. While highly useful as stand-alone solutions targeting one specific avenue of the waste collection process, an amalgamation of real-time status monitoring, dynamic route scheduling of vehicles and prediction of future bin filling rates to optimize collection can result in further improvements. Furthermore, as highlighted by Wange et al. [7], identification of primary sources of waste generation from real-time monitoring can also be realized. The present work therefore, aims to further refine the IoT-based waste collection process using real-time monitoring of garbage bins, prediction of future filling rates and dynamic route scheduling as one monolithic solution to ease operation. The proposed design employing general purpose Raspberry Pi hardware [8] and an application front-end can be used for real-time monitoring as well as in helping identify long-term waste generation trends in smart urban environments to streamline resource provisioning according to user demand. The next section presents the design of the proposed solution in detail.

III. Design

The present section highlights the design of the proposed IoT-based garbage collection system. An illustration of the primary components of the system is given in Fig. 1. The major modules of the system comprise of a sensor monitoring system, intelligent back-end processing module and a user front-end application briefly overviewed below.

(i) Garbage Bin Capacity Monitor: To monitor garbage bin capacity, ultrasonic sensors are used. The sensors are linked to the Raspberry Pi system mounted on top lid of garbage bins that transmit capacity information via Internet to the central server hosted at the relevant municipality.

(ii) Information and Analytics Server: The sensory information from each of the respective garbage bins is retrieved at pre-defined intervals and stored in the municipality server for further professing. An intelligent waste management scheme is devised to minimize the number of typical waste collection runs.

(iii) Monitoring Application: Analytic information is displayed to operators via a desktop-based monitoring application presenting real-time bin capacity and system generated updates to waste-collection routes. The same route information is also available to drivers via an android port of the application.

The waste management scheme as well as the monitoring sensors and front-end application are discussed further in the following sub-sections.

C. Waste Management Scheme

In comparison with earlier studies, the present design does not seek to completely overhaul waste management processes installed in any municipality. The proposed scheme instead utilizes machine learning analytics to predict bin-filling rate using historical statistics. The prediction is used in tandem with existing collection routes (road segments) to maximize the number of bins serviced. Optimal route selection using a predictive approach aims to reduce the overall number of collection runs over a default time frame, resulting in reduction in overall costs and bin-overflows. An illustration of the major functions of the proposed waste management algorithm is given in Fig. 2 while the corresponding algorithm is given in Fig. 3. To start off, the **Monitor()** function defines a threshold

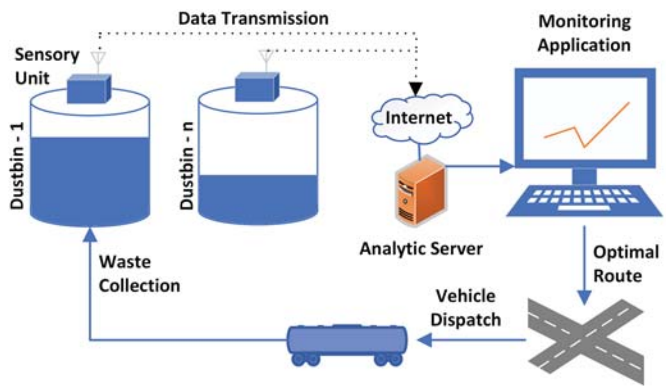

Fig. 1. Design Overview: IoT-Enabled Waste Management

of capacity for all bins, monitored at regular time intervals t_m with the respective bin status(es) stored in the central server. Two independent lists of bins are generated from this information: (i) a *bin collection list* for bins that have exceeded capacity threshold c_t and require servicing and (ii) an *auxiliary list* for bins that have not yet reached full capacity. All bins in the *collection list* are serviced by collection trucks and an **initial route** is accordingly devised by the **Route Analysis()** using Google Maps integration. To optimize the number of bins serviced and reduce future runs, the *collection list* is afterwards updated with additional bins from the *auxiliary list,* subject to fulfilling two conditions.

(i) The respective bin will exceed **capacity** c_p in a given future **time frame** t_p. The thresholds can be defined by the operator.

(ii) The respective bin is *within* a feasible distance of **initial route.** Feasibility is defined by a **fuel economy threshold** f again set by the operator.

Determination of (i) is done using two attributes, the historical filling rate of the respective bin and the time stamp of observation as input to C5.0 machine learning algorithm [10] in the **Predict()** function. A breach of c_p in t leads to computation of (ii). Provided that the respective bin conforms to f, the bin is marked for collection (placed in *collection list*). **Route Computation()** and **Collection Cost()** functions are used for the purpose as depicted in Fig. 3. Once the iteration is completed for the *auxiliary list*, the **initial route** has also been updated to a **final route** comprising of coordinates of all bins needing servicing, presented using the application front-end to the waste management operators as well as vehicle drivers on the mobile application. A two-step iterative process ensures maximum control over serviced bins using the introduced thresholds while still relying on dynamic scheduling. In contrast to prior schemes, alteration of c, t and f by operators according to operational concerns provides system scalability and the ability to intervene and update requirements as needed. The hardware and software implementation of the system is detailed in the following sub-section.

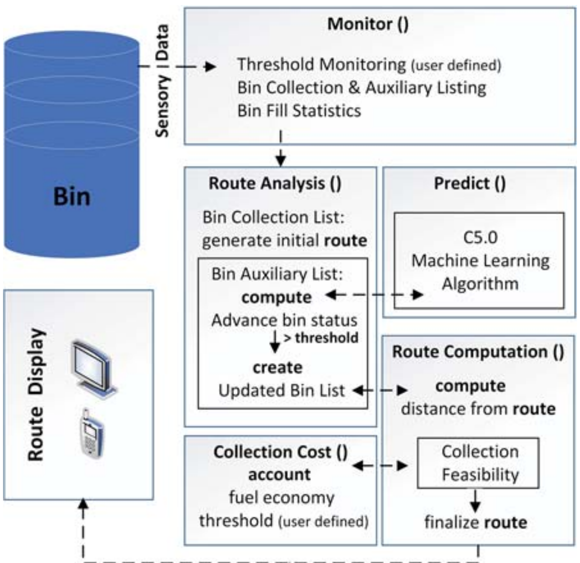

Fig. 2. Analytic Engine Components

```
main ()
start
define collection_time;
define bin_threshold;
define fuel_cost;
define cost_threshold;
while collection_time = TRUE;
 do:
    ∀ bin
    monitor (bin_status);
 if
    real_time_bin_status > bin_threshold;
    collection_bin_list += bin;
 else
    auxiliary_bin_list += bin;
 route_analysis (collection_list, auxiliary_list);
 display final_route;
end

monitor ()
 start
 ∀ bin
 ∀ days_of_week
 get real_time_bin_status;
      bin_fill_rate_statistics += real_time_bin_status;
 end

route_analysis ()
 start
 get collection_bin_google_map_coordinates <-- collection_bin_list;
 route = google_map_add_destination (collection_bin_list);
 for auxiliary_bin_list
     advance_bin_status = predict (bin_fill_rate_statistics);
            if advance_bin_status > threshold;
            updated_bin_list += bin;
            final_route = route_computation (updated_bin_list, route);
            else ignore;
 return (final_route);
 end

predict ()
 start
 input: bin_fill_rate_statistics;
 input week_day, time_of_day;
 C5.0_decision_tree --> bin_fill_rate_statistics;
 return (advance_bin_status);
 end

route_computation ()
 start
 ∀ bin ∈ updated_bin_list
 get google_map_coordinates <-- updated_bin_list;
 ∀ bin ∈ collection_bin_list
 get google_map_coordinates <-- collection_bin_list;
 fuel_economy = collection_cost (auxiliary_bin, collection_bin);
 if fuel_economy < cost_threshold;
    updated_route = route + google_map_add_destination (auxiliary_bin);
 else ignore;
 return (updated_route);
 end

collection_cost ()
 start
 compute real_time_distance = auxiliary_bin - collection_bin;
 fuel_economy = real_time_distance x fuel_cost;
 return (fuel_economy);
 end
```

Fig. 3. Algorithm: Route and Collection Cost Optimization

D. Hardware and Software Implementation

The hardware used for the system comprises of a Raspberry Pi [8] having Wi-Fi module and running standard Raspbian operating system. The depth of the garbage bins is monitored using a standard ultrasonic range sensor HC-SR04 [9], as depicted in Fig. 4. A Python based application was designed to retrieve the monitoring data from the ultrasonic sensor and send it to the central monitoring server at user-defined frequency t_m. The Raspberry Pi connects to the Internet using Wi-Fi and sends monitoring statistics in encrypted format (triple DES) to protect information compromise. The Wi-Fi module only switches ON when data is to be transmitted to increase device power efficiency. In terms of software, the server side runs standard Apache webserver. A front-end is designed in PHP to present status. A graphical snapshot of the desktop front-end is given in Fig. 5. The waste management algorithm presented in Fig. 3 is implemented in Python and integrated with Google Maps using Google APIs to map bin coordinates to real-time routes. A similar android front-end is also developed presenting the **final route** to collection drivers on android-based mobile platforms. Different status flags were used to identify bins in the *collection* and *auxiliary lists*. The next section discusses the evaluation of the software, hardware and the proposed scheme in detail.

IV. Evaluation

To determine the efficiency of the proposed design, the IoT-based waste management system was subjected to a trial run within a specific area of a cooperating municipality over a span of ten days. A total of *thirty-eight* residential bins were mounted with relevant IoT-sensors and connected to public Wi-Fi. The IoT-enabled bins formed part of eleven *existing route segments* (of different lengths) spanning 105.4km. The eleven collection routes were serviced daily by the municipality waste management company vehicle within an average time span of 220 minutes. A colour-coded scheme of the respective segments is given in Fig. 5. The default start and end-point are the waste collection facility is given by the red pointer. During the trial period, the frequency of waste collection as well as changes in fuel economy were observed. A highlight of quantitative and qualitative results is presented in the following sub-sections.

E. Results

The proposed system was implemented over the eleven route segments (and corresponding bins) between 15/03/2018-25/03/2018. Maximum bin fill threshold was set to 67.5% of capacity. Each bin being of 80cm height, translated to a maximum fill threshold c_t of 70cm. The predictive capacity threshold c_p was set to 33.75% or half of c_t. The capacity was monitored by setting t_m to 60 minutes, while predictions were made for future twenty-four hours i.e. $t_p = 24$ hours. One-hour time span for monitoring (t_m) was selected in the trial to increase the energy efficiency of Raspberry Pi devices, in the present case powered by battery packs. All battery packs were serviced by the research team every two days to ensure non-interrupted data collection. Finally, the fuel economy threshold f was set as *<1% fuel cost* of the **initial route**. Fuel cost per kilometre of *collection distance* was set at default value given by truck meter. As depicted in Fig. 5, each bin was identified using a generic ID for ease of identification, mapped to the MAC address of the respective Raspberry Pi interface. An overview of the data collected for BIN-1 and stored in the central server is presented in Table 1. Three collection flags were used: green, red and amber. Green collection flag indicates the bin is not in the *collection list* and collection is not

Fig. 4. Hardware Implementation: Raspberry Pi and Ultrasonic Sensor

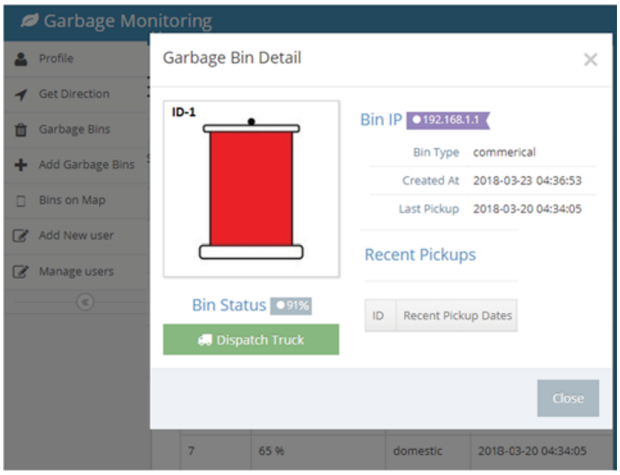

Fig. 5. Monitoring Application: Desktop Front-End

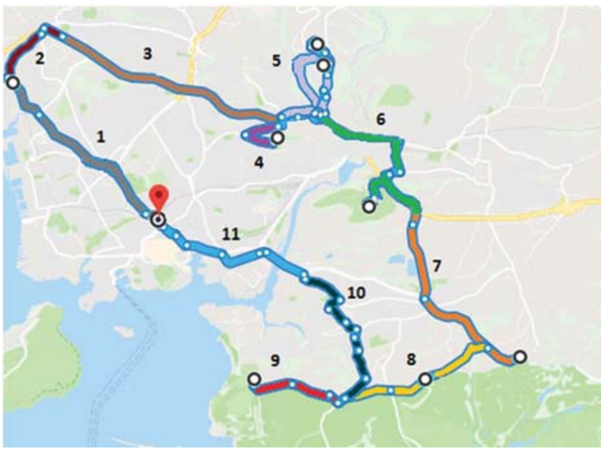

Fig. 6. Municipality Area: Eleven Route Segments (anonymized)

TABLE I. BIN-1: REAL-TIME CAPACITY AND SERVICE STATUS

Time Stamp	BIN-ID: 1			
	Status c (Used)	*Prediction c_p (t_p= 24 hours)*	*Route Segment*	*Collection*
20/03 – 08:15	11.75%	14.25%	1	
…..	….	….	…..	…..
23/03 – 04:35	91%	99%	1	
…..	….	….	…..	…..
25/03 – 07:25	49.3%	59.2%	1	

needed. Red indicates that the bin has exceeded c_t and is ready for collection. Amber indicates that the bin has conformed to the two pre-set conditions discussed earlier i.e. $c_p \geq 33.75\%$ and $f < 1\%$ of **initial route** cost. Anticipated bin-levels are determined by feeding two features, *time stamp* and *present status* into C5.0 algorithm to predict the bin-level c_p for next twenty-four hours. In Table 1 we can observe that BIN-1 status recorded on 20/03/2018 at 08:15hrs is green with relatively low filling predicted for the following 24 hours. Therefore, collection is not required. On 23/03/2018 at 04:35hrs the bin status is at 91% and requires immediate collection. This would trigger a route generation where BIN-1 will be serviced along with all bins exceeding c_t and any other bins not part of the route but in the *auxiliary list* and being *feasible* for collection. Finally, on 25/03/2018 at 07:25hrs the bin capacity has been consumed at 49.3% with a prediction of 59.2% for the following 24 hours. The bin will therefore be up for collection depending on meeting the *feasibility* criteria. To benchmark the cost savings and fuel economy of the proposed system a comparison was made between manual and IoT-enabled collection runs over the ten-day time-frame. The graph in Fig. 7 depicts the changes in route-segments traversed over the respective period. For each day of trial, it can be observed that the number of segments covered using real-time IoT analytics (information) is fewer that the default value of servicing eleven segments. On day 1 and day 5 only four route-segments were traversed by the service vehicle as opposed to the default value of eleven. Furthermore, when default route-segments were traversed these too were partial (given by blue indicators) depending on the determined bin service requirements. Of the observed time period, on day 4, the collection vehicle drove over nine full route segments, which was the maximum value observed. Hence the overall efficiency can be corroborated as ranging approximately between a minimum of at least 18% and a maximum of 63.4% as per the route segment service saving. A further analysis of route economy and fuel efficiency is presented in Fig. 8. It can be observed that savings in distance ranged up to 27 km on particular days depending on the size and number of route segments traversed. This measure therefore, amounted to a saving of approximately 26% of the total 105.4km default route. The corresponding fuel efficiency when computed ranged up to 46%, again depending on the number and size of route-segments serviced by the waste management vehicle. Table 2 presents an overview of the time saving realized due

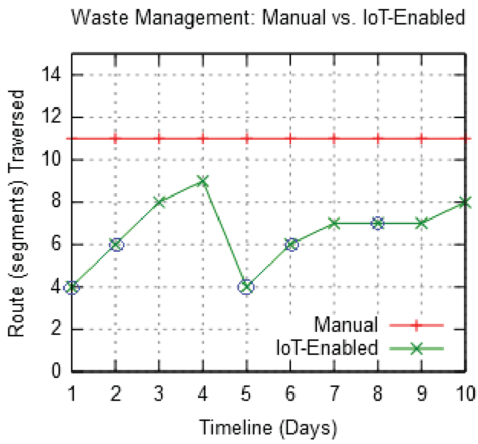

Fig. 7. Default Waste Collection Scheme (Eleven Route Segments)

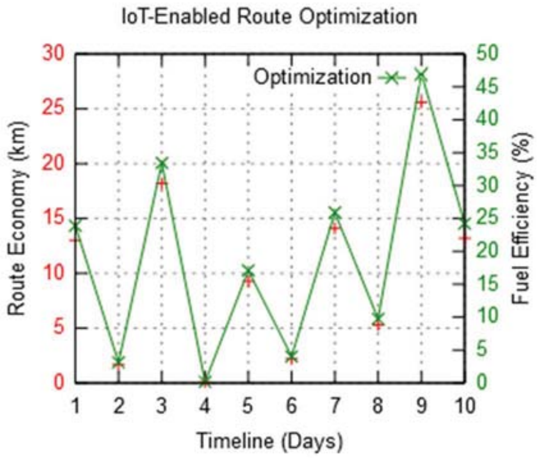

Fig. 8. IoT-Enabled Route Optimization

to the deployment of the proposed solution. During the trial period, it was also observed that the savings in time economy were substantial. As given in Table 2, while on day 4 no time savings were reported due to collection from nine route segments, while on day 9 the total time saving amounted to approximately forty minutes (18%). The average time savings over the entire period approximated at 16 minutes of saving per day. Overall in terms of routes traversed, the fuel economy and time saving, the proposed design offered substantial savings over the manual approach of emptying bins from all route segments on a daily basis. In addition to economization of the waste collection process it is also worth noting that accurate monitoring and management of waste collection contributes to overall cleanliness in smart cities. A qualitative discussion of the results follows in the next sub-section.

A. *Qualitative Analysis*

Further to earlier discussion of empirical results related to efficiency in cost savings, the experimental also revealed qualitative benefits due to the use of IoT-based waste management in the studied urban area. Smart city environment can be considered as an merger of real-time sensor-based monitoring with intelligent analytics to improve habitation. Waste collection management is a focal area of concentration in any urban environment preparing to join the smart city narrative. In the present study the mounting of residential waste bins with IoT sensors for real-time monitoring significantly improved collection efforts, streamlining resources where most needed while reducing costs. Additionally, decrease in vehicle (collection truck) runs that navigated only essential routes, directly contributed to discounting road traffic, lowering pollution as well as noise levels, the fundamental requirements of a greener environment. Furthermore, as highlighted earlier, sensory information combined with analytics can bring fruition to achieving smarter administration of essential urban necessities as well as aid managers in future planning. The waste statistics recorded in the present study for example, gives administrators additional leverage in understanding the waste generation rate of residential areas that may be subsequently used in intelligent placement and determination of bin sizes as needed. Subscription models can also be introduced using these statistics to incentivise lesser waste generation and penalize anti-environmental behaviour. An extended deployment of the designed solution can generate more useful data to analyse and automate the threshold limits that were manually set in the present design. Back-end analytics therefore, is as important as the front-end sensors, and IoT-based engineering facilitates the means to construct and pursue intelligent policies.

TABLE II. TIME EFFICIENCY RECORDED

Day	**Observed Parameters**	
	Route Saving (km)	***Time Saving (mins)***
1	14.21	18.7
2	2.1	3.5
3	19.1	28.2
4	0.35	0
5	10	14.2
6	2.5	3.3
7	14.65	21.1
8	6.1	9.3
9	27.2	39.8
10	14.7	21.3

Ongoing challenges in IoT-based implementations however, increasingly focus on scalability of use, energy efficiency and security [2][7]. In the present study utilization of off-shelf Raspberry Pi modules realized a cost-effective solution for future implementations by the municipality, making the design scalable. While power packs were used and serviced frequently in the employed devices, utilization of miniaturised Raspberry Pi models along with solar-cell solution can offer substantial longevity to sensor life. Using low-power mode monitoring as well as transmitting data at pre-specified intervals can further add energy efficiency to the design. In terms of security although the transmitted data in the present design was encrypted, additional work is needed to understand the security issues inherent in IoT infrastructure and the repercussions that a cyber-attack might have on waste collection management in councils. The employment of IoT analytics therefore, is a growing phenomenon and as reported in the present work, offers significant advantages in dynamically provisioning resources and increasing cost efficiency to tackle waste collection management in smart urban areas.

V. CONCLUSION & FUTURE WORK

The present work investigated the utilization of IoT-enabled sensors and machine learning analytics to streamline resource allocation in urban waste management. The results recorded from a ten-day trial of the proposed design in a municipality area under observation delivered significant optimization in fuel and time costs. The substantial gains noted as a result of employing IoT and data analytics over manual fixed waste collection scheduling leads us to recommend further adoption of IoT-based systems for smart city waste management. In future work, IoT power efficiency will be trial-tested using solar energy and the proposed solution extended over multiple city areas to further ascertain design scalability as well as improve monitoring thresholds.

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