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Optimal Route Recommendation for Waste Carrier Vehicles for Efficient Waste Collection: A Step Forward Towards Sustainable Cities

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ABSTRACT The exponentially growing population, urbanization, and economic development have led to the rising generation of municipal solid waste. Municipal solid waste management is thus a significant hurdle for urban societies as it consumes a large chunk of public funds, and, when mishandled, it can lead to environmental and social hazards. Some of the prerequisites required for effective waste management are the monitoring of bins, timely collection of bins, and prioritization of those areas which produce more solid waste. In this paper, we propose an optimal route recommendation system for waste carriers vehicles to effectively collect solid waste based on the profile of a particular area. This article contributes with a multi-objective optimization approach to generate a route by minimizing the route distance and maximizing the amount of waste. Then, a family of evolutionary methods is employed to solve the proposed objective function and find the optimal route for waste carrier vehicles. The experiment is carried out on the real-world solid waste data of Jeju Island, South Korea. The data is processed to predict the behavior of people of a specified grid location in terms of waste disposal. Therefore, the recommendation system caters to the predicted waste across a set of bins inside the area, and considering the constraints such as total allowed distance and time, proposes a route that is best in terms of distance (fuel consumption) and waste collection. Different use cases are illustrated to signify the proposed system, and results indicate that it can be a step forward for the implementation of smart cities, which is the goal of Jeju Island.

INDEX TERMS Waste management, route optimization, smart cities, sustainable development, green projects, Jeju Island.

I. INTRODUCTION

Cities across the globe are welcoming a new era of transformation in which intelligent technologies are used to interconnect residents and their surrounding environment, referred to as smart cities. Smart cities aim to improve urban agglomeration by using decision support systems. A city is recognized to be "smart" if it uses real-world and real-time data collected from various city services to make decisions and devise policies intelligently [1]. Solid waste management is among the most vital areas in smart city transformation due to its significant contribution to the budget of local government and associated risks to the environment [2], [3].

The development of an effective system for solid waste management is considered a significant hurdle in terms of economies development [4]. The situation is exacerbated by the increasing production rate of solid waste due to the rapid urbanization and substantial growth in population [5], [6]. Similarly, inadequate financing [7], poor waste disposal attitudes of citizenry [8], and lack of political will [9] also contribute towards such hazards. These challenges go

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beyond the ability of local authorities in developing countries to manage solid waste [10] effectively.

As part of smart city transformation, Jeju Island of South Korea was nominated for the 2016 smart city Asia Pacific awards, which recognize the outstanding efforts towards smart city transformation in the Asian Pacific region [11]. According to statistics, the population size of the island is around 660,000 people, but over 15,000,000 people visit per year. It is a beautiful island which has been attracting tourists from around the world due to its serenity and unique culture. According to the annual report issued by the municipality of Jeju, about 628 tons of solid waste are collected each day, out of which 34% is only food waste [12]. The solid waste produced contains trash or garbage such as wood, product packaging, empty bottles, used tires, and leftover food, to name a few.

According to a new report [13], Jeju island has been piling up from waste, which affects not only visitors but also the seawater. The Island authorities are happy to host more and more visitors. However, this constant growth of solid waste has been an enormous challenge and always pushing authorities to tackle it and come up with a solution that could efficiently manage the situation. Therefore, Jeju Province is undertaking many projects regarding this challenge as part of the transformation process.

The accumulation, processing, and disposal of waste generated by domestic people and tourists are considered highly vital for the authorities. The data are consumed by the Municipality of Jeju to form legislative policies. In the majority of the developed nations across the globe, the use of an integrated municipal solid waste management system has been instated to efficiently manage solid waste and contribute towards maintaining a certain level of hygiene in areas [14]–[17]. The municipality, as part of the majority of stakeholders, should play an integral role in the generation, collection, processing, and disposal of waste for the efficient performance of the integrated waste management systems. Such policies are crucial in terms of the reduction of overall cost and maintaining a certain level of hygiene in the town as outlined in many studies [18]–[20]. Overall efficiency in the management of waste depends on adherence to local acts on waste disposal and management [19], [21], [22]. As part of the smart city transformation project, a variety of efforts have been put forward, but they are mostly related to smart tourism as it is the most significant contributor to the local budget [23], [24]. However, there is a clear gap for an intelligent and optimal waste management system, which has the potential to save a considerable chunk of the budget.

This paper is thus a step forward towards a smart and optimal waste management system to consume the historical data for making intelligent decisions. The research objective and motivation of this work is to contribute to the state-of-the-art methods with a new multi-objective optimization model which simultaneously reduces the distance (fuel consumption) of the route and maximizes the waste amount. It then designs an optimal route recommendation system that takes the proposed objective function and suggests routes that have a high waste amount in less time and distance. The paper uses a real dataset provided by the municipal authorities. The dataset has data across 2017 to 2018 for specific attributes such as waste amount generated monthly, weekly and daily inside a local grid. Additionally, it has information about the grid, such as the population of the grid, the gender of residents, and age groups. Based on these parameters, prediction algorithms are applied to infer the amount of grid generated for a particular grid. The predicted waste model, along with the set of constraints, are used to model a multi-variable objective function that minimizes the distance (cost) and maximizes the waste collection for a particular grid. Therefore, this work makes use of decision support systems as part of smart city transformation to help the municipality to devise smart policies and focus more on those grids, which produce more waste and frequently cause an overflow in the bins.

II. RELATED WORK

Several studies have addressed the problem of growing solid waste by employing different intelligent techniques. Among the notable solutions is the optimal placement of bins, the optimal frequency of waste collection, the behavior profiling of residents, to name a few [25]. With the advances in the Internet of Things (IoT) technologies, the job of monitoring the status of waste bins is becoming pretty easy. The most notable effort is the introduction of an IoT-based smart garbage system (SGS) to reduce the amount of food waste. In an SGS, battery-based smart garbage bins (SGBs) exchange information with each other using wireless mesh networks, and a router and server collect and analyze the information for service provisioning, which could reduce the amount of waste by 33% [26].

Another notable effort is the introduction of the decision support system for efficient waste collection from inaccessible areas within smart cities [27]. The research is based on the block status of bins, and the truck driver finds those bins and reports them. A similar effort worth mentioning is the development of a cloud-integrated wireless garbage management system for smart cities. The proposed system centrally monitors the temperature, humidity, flammable gas concentrations (or smoke), fire detection, and garbage fill volume in waste bins with the help of wireless sensing nodes placed at remote locations in the city [28]. Another challenge is the energy-efficiency of such a system not to exceed the limited requirement required by the smart cities. Kristano *et al.* introduced dynamic routing in a municipal waste collection using a smart trash bin in a cost-effective and energy-efficient manner [29]. However, ordinary smart trash bin works by measuring the volume of trash with a static time interval, which causes high power consumption and short battery life. In an another effort, IoT-enabled system architecture is proposed for dynamic waste collection and delivery to processing plants or special garbage [30].

Unlike in the past, where waste collection was treated in a rather static manner, a top-k query-based dynamic scheduling model to address the challenges of near real-time scheduling driven by sensor data streams has been introduced. All of these studies are proposed to ensure a certain level of hygiene of areas. However, these studies monitor the bins and report it once the overflow occurs. In other words, they are more of remedying the problem rather than avoidance in advance.

The avoidance of overflow in bins is made possible with the integration of IoT and machine learning technologies. The data generated from sensors installed in waste bins are collected on the cloud, and machine learning algorithms are performed to analyze the behavior of people. Some of the notable efforts include the modeling and prediction of regional municipal solid waste generation and diversion using machine learning approaches [31]. Shyam *et al.* [32] present a waste collection management solution based on providing intelligence to waste bins. These bins are equipped with sensors which read, collect, and transmit massive volume of data over the internet. Such data, when put into a spatio-temporal context and processed by intelligent and optimized algorithms, can be used to manage waste collection mechanism dynamically.

The use of Geographical Information System (GIS) technology has also been witnessed in the recent past for optimal placement of bins in a residential grid. Aemu *et al.* analyzed the impact of optimal bins location using GIS approaches and proposed that it has a direct impact on the overall cost, residents' convenience and satisfaction, efficient collection for waste carrier vehicles, to name a few [33]. Similar approaches are backed by Boskovic and Jovicic [34] and Erfani *et al.* [35] to solve the case studies based on urban locations in Serbia and in Iran, respectively. A more young study has been conducted by Imran *et al.* [36] for Jeju Island. In this study, quantum GIS is used to investigate the behavior of people towards waste disposal and the prediction of waste for a certain residential area using predictive analytics. However, the authors also highlighted the need for efficient waste collection in an optimal and intelligent way.

Although the problem of optimization often involves contradicting variables and constraints, there are different mathematical and heuristics techniques to find the best optima for the objective function. There are a variety of techniques for solving the objective function. The problem in which heuristics are involved, evolutionary algorithms are used more often as compared to mathematical techniques due to their applicability in all cases [37]. The most notable among the family of these algorithms is particle swarm optimization (PSO), which deals with the collection of flying particles (swarm) - Changing solutions in such a way to form a search area that contains possible solutions to the problem. The particle moves in the search space to get the global optimum. Each particle keeps track of its best solution, personal best (pb), and the best value of any particle, global best (gb). Each particle modifies its position according to its current position, current velocity, the distance between its current position and pb, the distance between its current position, and gb [38]. Another popularly known algorithm is the Genetic algorithm in which the population of individuals evolves through fitness function to give rise to a more fitter solution according to the defined rules of selection, mutation, and crossover [39]. BAT is a relatively new algorithm based on the hunting behavior of bats. The prey of bats is the solution, and bats move to find the best prey [40]. An extensive literature on the modified versions of these algorithms also exists as, for some optimization problems, these core algorithms tend to be on a slower side [41], [42].

As discussed in the above-mentioned research studies, IoT helps in tracking the status of bins, whereas machine learning forecast the behavior of residents and the possibility of bins overflow. However, policymakers also consider the best solution among possible alternatives in terms of cost and time. In other words, if five bins are overflowed on two specific routes, the decision to prioritize the route based on the severity of consequences is also one of the roles of policymakers. In this paper, the trained model, whose role is to predict the waste amount in a particular bin, is applied as an input to the objective function to find a route that not only collects the maximum waste amount but is also fuel-efficient. This collective idea of the predictive optimization technique for waste management avoids the overflow of waste bins. It helps in ensuring the required level of sanitation in Jeju, which to the best of the authors' knowledge, is the first step towards green and clean Jeju Island.

III. METHODOLOGY FOR OPTIMAL ROUTE RECOMMENDATION SYSTEM

In this Section, the methodology of the proposed work has been explained. As mentioned in earlier sections, decision support systems are vital for smart cities' transformation as they help in devising intelligent policies based on historical knowledge. In this paper, historical data of waste generation for residential grids are utilized to predict the behavior of people towards waste disposal and accordingly manage the optimal waste collection. Information such as population of grid, male and female members, grid coordinates, the waste amount for weekdays, and monthly data for 2017 and 2018 constituted the main features in the dataset. The age groups of the population varied from under ten years, 10-25 years, 26-40 years, 41-65 years, and over 65 years. The raw data had some important missing features, such as total waste across the whole span of time, and there were also missing values. Therefore the data was preprocessed, normalized, and required fields necessary for the waste profile of a certain grid were derived. The summary of the input features and derived features are shown in table 1.

The methodology of the proposed work is shown in Figure 1. First off, the data was collected from the grids for the year 2017 and 2018. Considering that the initiative of Jeju smart city started in 2016, this was the earliest dataset that we could use for the analysis. The data contained features that are shown in the input box. The raw data was provided to the next

TABLE 1. Input dataset's base and derived features summary.

Feature	Description	Feature Type
GID	The unique identification number corresponds to a particular residential grid	Base
Population	Total number of people in grid	Base
Single Family	The number of single families in the residential grid	Base
House Count	Total House count in a residential grid	Base
Gender-wise Population	Total population of male and female members of the grid	Base (2 features)
Age Group Distribution	Total population of certain age group from under 10 children to over 65 senior members of the grid	Base (5 features)
Monthly Waste Distribution	The waste amount in tons for each months across 2017 and 2018	Base (24 features)
Day-wise Distribution	Total waste amount in tons for each day across 2017 and 2018	Base (7 features)
Grid Coordinates	The coordinates of residential grid, i.e., Top, left, right, bottom, center	Base (5 features)
RFID	RFID of the Bin located in grid	Base
Convenience Value	The distance from the bins to the houses	Base
Location	The latitude and longitude of the grid	Base (2 features)
2017 Waste	Waste amount of the year 2017	Derived (monthly aggregation)
2018 Waste	Waste amount for the year 2018	Derived (monthly aggregation)
Weekdays Waste	The amount of waste disposed off on weekdays	Derived
Weekend Waste	The amount of waste disposed off over weekends	Derived
Season-wise Waste	The amount of waste for each season across 2017 and 2018	Derived
Grand Total	The total aggregated amount of waste for each residential grid	Derived

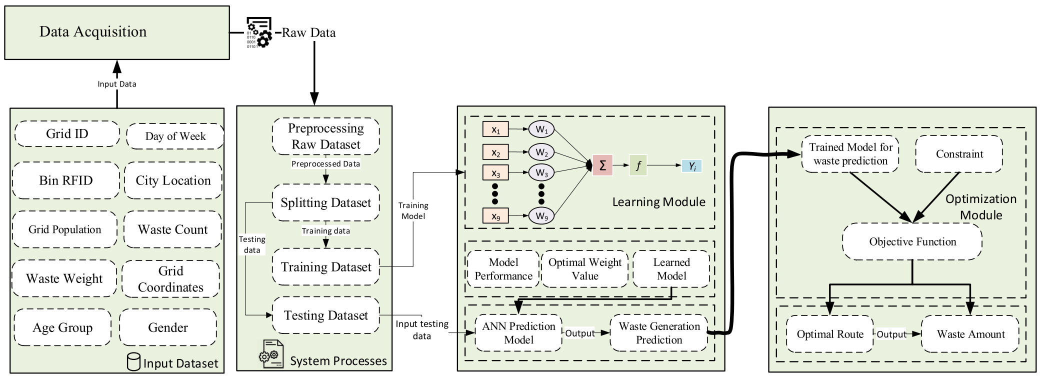


FIGURE 1. Methodology of optimal route recommendation system.

step, where some preliminary preprocessing was performed. The preprocessing includes removing the missing entries and deriving features from the aggregation of input features. The preprocessed data is supplied to the next module, which is the prediction module. The prediction module applied a variety of prediction algorithms on the data to compute the waste prediction model, which has the best accuracy among its counterparts. The algorithm whose performance was best among the lot is saved and applied to the next phase. The final module is the optimization module, which takes some constraints and the prediction model and finds the optimal route, which is the best in terms of waste collection and distance, which are the objectives of this work.

TABLE 2. Summary of symbols and notation used in different algorithms.

Symbol	Description
R	Candidate Route
P	Population of Grid
L	Location
Lat	Latitude
X	Input
D_c	Covered Distance
w	Weight of each input attribute
C	Constraints
M	Trained Model
W	Waste Amount in grams
Long	Longitude
Y	Output
D_a	Allowed Distance
G	Grid information

IV. OBJECTIVE FUNCTION FORMULATION FOR OPTIMAL RECOMMENDATION SYSTEM

In this Section, the objective function is formulated, and the constraints affecting the objective functions are outlined in detail. The objective of the route recommendation system is two-fold; first, the waste collection should be maximum, and second the distance covered by the truck should be minimum. We also consider the difference between allowable distance and the covered distance, which should also be minimum in order to overcome resource under-utilization. The data structure which will be used in the formulation of the objective function is summarized in table 2.

The design variable of the objective function is shown below.

$$X = [M, C]$$

The input to the function is the predicted model and Constraints. Constrains can be allowable distance, capacity of truck, grid assigned to the truck and maximum time for the route as shown below

$$C = [D_a cGt]$$

The objective function is a function that is dependent on route distance, collected waste amount, and the difference between allowed distance and route distance, as shown below

$$Y = (R, W, \sigma)$$

where σ is the difference between allowable distance D_a and candidate route distance R. Thus, the objective of the system is to minimize the candidate distance, maximize the waste collection, and minimize the difference between allowable distance and candidate route distance, as shown in equation (1).

$$f(x) - minR + maxW + min(D_a - D_c) \tag{1}$$

A route R is the series of different locations $l_1, l_2, l_3 \ldots L_N$, where l_1 is a representation of location in terms of its latitude and longitude as shown below.

$$l_1 = f(Data[lat_1], Data[long_1])$$

The distance from l_1 to l_2 is computed based on Haversine of the central angle between them as shown in below equation (2).

$$hav(\frac{2xd}{D}) = hav(lat_2 - lat_1) + cos(lat_1) \times cos(lat_2)hav(long_2 - long_1) \tag{2}$$

The distance is thus given by (3).

$$d = \frac{D}{2}hav^{-1}(hav(lat_2 - lat_1) + cos(lat_1)cos(lat_2)hav(long_2 - long_1))) \tag{3}$$

The distance of a given route $R = l_1, l_2, l_3 \ldots L_N$ is given by (4).

$$R = \sum_{i}^{n-1} d(l_i, l_{i+1}) \tag{4}$$

Putting the value of R from equation (2) in (4), we get (5)

$$R = \sum_{i}^{n-1} D/2hav^(- 1)(hav(lat_{i+1} - lat_i) + cos(lat_i)cos(i + 1))hav(long_{i+1} - long_i) \tag{5}$$

Another objective is to minimize the distance in such a way to increase the waste amount subjected to the constraints.

$$y = min(\frac{r}{w}) * \sigma \tag{6}$$

The waste amount is the function of a waste prediction model with Maximum Accuracy. We will compute the best model in the subsequent sections and find its hyper-parameters and put it in the model mathematical form. For instance, if the model is linear regression, the model equation will be

$$y = wX + I \tag{7}$$

where w and I are the hyper-parameter of the line, the line is considered best fit if all the points reside on it or very close to it. For instance, after model training, the w=2 and I=4, the waste amount for the location will be the function of $2X + 3$, where X is the set of input features. Considering the values of R and W, the objective function is shown in (8).

$$y = min(\frac{R}{2X + 3})(D_p - D_c) \tag{8}$$

However, the value of denominator can be changed based on the best performance results.

V. DATA PREPROCESSING, FEATURE PRIORITIZATION, AND PREDICTION

In this Section, we use the dataset, preprocess it, and select the features which are strongly correlated with the waste amount and perform predictions with a variety of popular prediction algorithms. As discussed in table 1, the dataset has attributes related to a particular grid. Figure 2 shows the flow of the preprocessing. In the waste analysis phase, the raw dataset is provided to the preprocessing unit. The data is cleaned, and the missing entries are handled appropriately. In this paper, we remove the records which have missing values. The cleaned data, along with the dataset attributes, are considered for further processing. Since the dataset does not contain a direct attribute for total waste weight, which is eventually going to be the output column of the prediction model, it is mandatory to compute it using the available waste amounts. The monthly data are summed to make a grand total. Similarly, as part of the preprocessing, season-wise waste, weekend waste, and weekdays waste are also computed to draw patterns of waste for these particular periods and helps the authorities to devise plans based on the analysis.

Once the dataset is cleaned, and various attributes are derived, the next step is to select the feature and reduce the dimension of the dataset by removing irrelevant features from the feature space. There are some common techniques for feature reduction, such as correlation analysis and principal component analysis (PCA). In this work, we analyze the correlation of all features with the target feature and selected those features which have correlation index 0.30 or more. In the case where more than one feature has a similar correlation coefficient, any of them is selected. The sorted matrix of correlations of the top 10 features with the target feature "Grand total" columns is shown in Figure 3.

Table 3 shows the summary of selected final features, which play a pivotal role in predicting the waste amount inside a certain grid. The amount of grid thus heavily depends

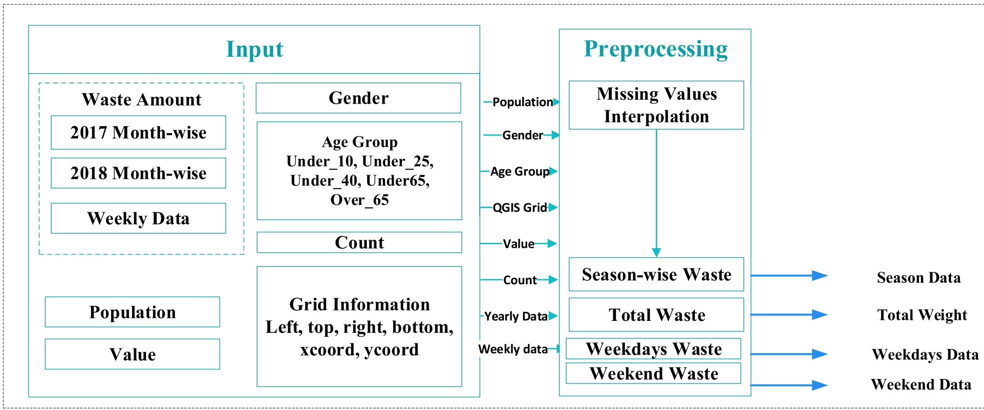


FIGURE 2. Dataset feature selection and processinge.

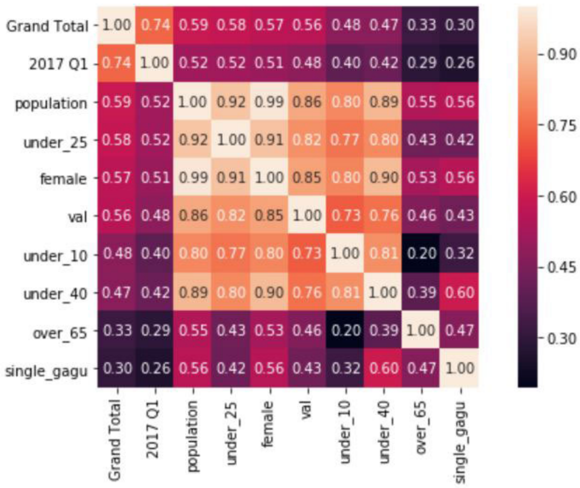


FIGURE 3. Feature prioritization and selection.

TABLE 3. Summary of Features which has the leading impact of the output feature.

Features	Description	Correlation Index
2017 Q1	The strongest correlated column is spring season of the year.	0.74
Population	The second strongest correlated column with the output column is population	0.59
Under 25	The waste amount correlation with people with age less than 25 years	0.58
Female	The waste amount correlation with female population	0.57
Convenience Value	This value represents the convenience of a certain location based on the distance to the nearest bin	0.56
Under 10	The waste amount correlation with under 10	0.48
Under 40	The waste amount correlation with under 40	0.47
Over 65	The waste amount correlation with over 65	0.33
Single Family	It represents whether a a family is single or multi-family.	0.30

on the population of the area, the season of the year, the distance of houses from the central waste bin, and the number of people of different age groups.

Once features are selected, the next step is to use different prediction algorithms and apply them to the selected features. The algorithms are taken from a variety of popular regression algorithms. Some of them are Support vector regression (SVR), Lasso Regression, Linear Regression, KNeighbour Regression, Random Forest, and Gradient boost, to name a few. For prediction, we have divided the dataset into two different chunks. We use 75% of the data as the training set and the remaining 25% of the data as the testing split, as it is the optimal ratio for the dataset size that has been used in this work. The selection of the optimal split depends on the size of the dataset, and based on our dataset, a 75% training set gives the best accuracy. Figure 4 shows the methodology and flow of the prediction process.

First, the selected features are split across two subsets; test split and training split. The set has been provided to the afore-mentioned algorithms, and the results are shown in Figure 5. Some of the algorithms like Ridge and Lasso perform very well, but they are not generalizing the patterns and causing overfitting. The support vector regression algorithm produces the best results among the lot and thus considered for the optimization model, as shown in Figure 5.

VI. OPTIMIZATION FOR TRUCK CARRIERS ROUTE RECOMMENDATION

In this work, we will optimize the route of the truck carrier based on the formulated objective function. The optimization algorithms Total predicted waste of a grid amount, Truck current location, Truck current capacity, Truck total capacity, truck nearest bins, Total waste collected, Frequency of bins collected, to name a few. Based on the above constraints, the objective function computes an optimal index, which minimizes the route distance and maximizes the waste amount.

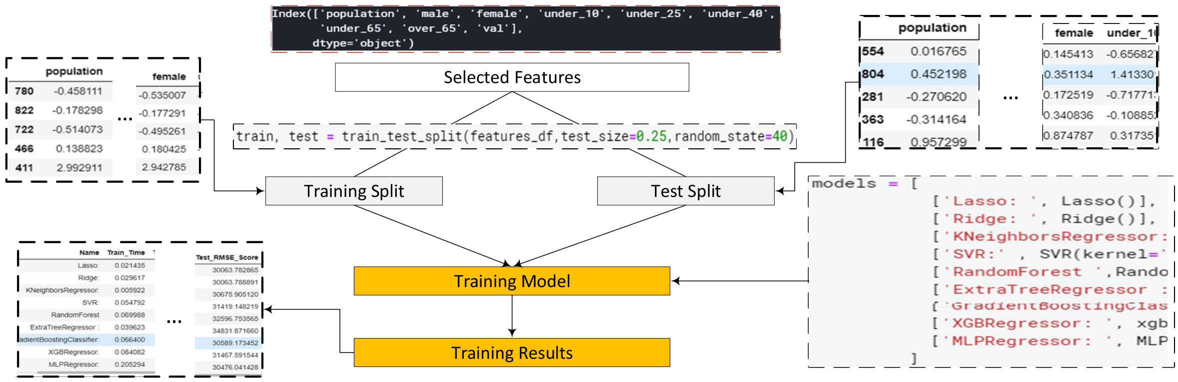


FIGURE 4. Implementation process of prediction.

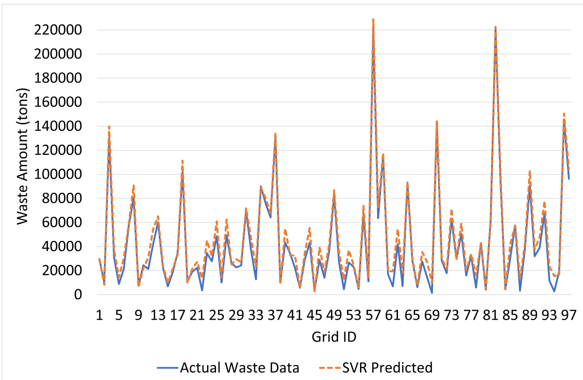


FIGURE 5. Prediction results.

A recommender application is implemented to take the current truck location, truck current capacity. The nearest bins, their current capacity, and their expected capacity will also be noted. Based on the above constraints and data, the recommended route will be generated, which will be notified to the truck owner. The formulation objective function is considered below.

$$y = min(\frac{R}{\sum(a_i - a_i^*).K(x_i - x) + b})(D_p - D_c)$$

where a and a^* are Lagrange multipliers, and K is support vector kernel. The model takes input features and predicts the waste amount using the trained support vector machine model. The predicted amount of waste alongside constraints are given as input parameters to the objective function.

The flow of the recommendation system is shown in Figure 6. First off, Jeju Island food waste is provided as an input. The data which contains different columns, as described in earlier sections, are preprocessed. The preprocessing includes the derived fields, computation, and interpolation of missing entries. Once the data is processed, the constraints, which are truck capacity, total distance, and others, are given to the objective function. The objective function minimizes the route distance and maximize the waste amount and recommend the possible list of routes with optimal indices.

A. USE CASES RESULTS FOR OPTIMAL ROUTE RECOMMENDATION SYSTEM

The use cases for the route recommendation system is based on the objective function as defined in 8. For instance, if the allocated distance is 20 KM, then the route with 5 kilometers will have a difference of 15 KM. If this route produces a collection of 70 kg, then according to formula, then the total waste tw.

$$tw = 5 * \frac{15}{70} = \frac{75}{70}$$

The optimization algorithms considered in this work compute the optimal index based on the above-mentioned equation for all the possible routes between the source and destination, and in the end, select the minimum index. The pseudocode for implementing the proposed optimal route is shown in pseudocode 1.

The flow of operation is shown in Figure 7. The initial location and allocated distance are given as a set of constraints. Afterward, the shortest list of routes, along with their waste collection, is computed based on particle swarm optimization, genetic algorithm, and BAT. For every candidate route, the optimal index is computed, and in the end, the route with the minimum optimal index value is selected as an optimal route.

In the following subsections, we will present the use cases for which the proposed route recommendation is simulated. We consider three different categories of cases; intra-grid short route recommendation for grids with a small geographical area, intra-grid long route recommendation for grids with a large geographical area, and finally for inter-grid routes which span across different grids.

1) CASE 1: INTRA-GRID SHORT ROUTES

Firstly, the route recommendation application is run for grids with small geographical areas. Suppose that the initial location is Neonghyup 5 street 7, the final location is Jinkunnam street 1, and the allowed distance is 5 kilometers. The top 3

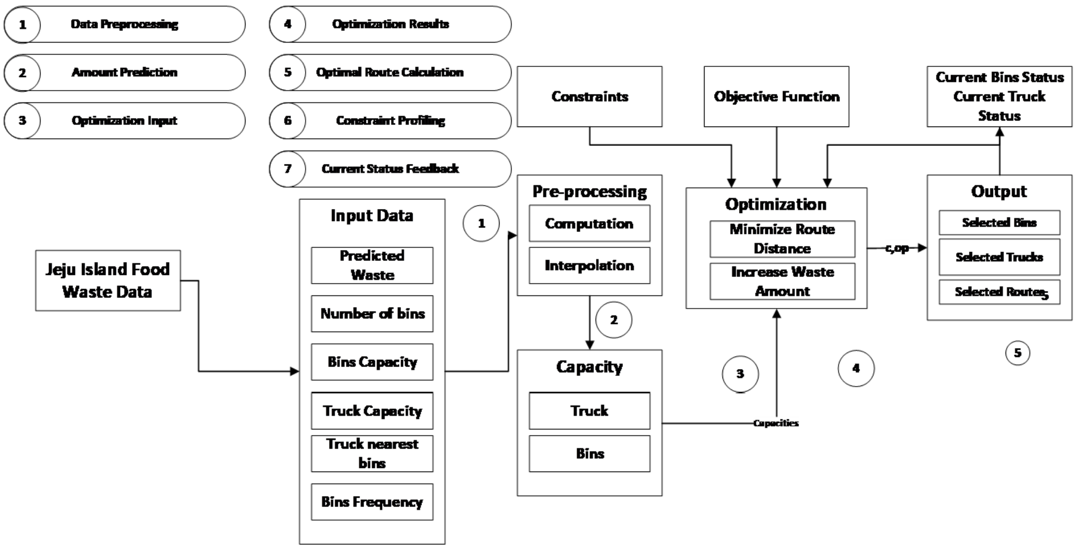


FIGURE 6. Optimization flow.

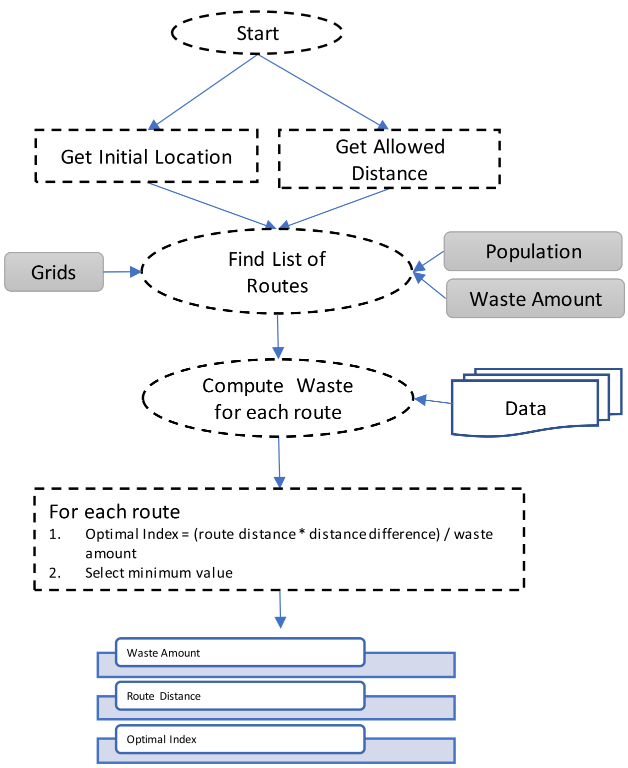


FIGURE 7. Route recommendation usecase flow.

optimal routes are given in Table 4. Route 2 is the recommended route and is shown in Figure 8 on the Naver map. The optimal route, in this case, is route 2, which has the minimum optimal index because it has more waste compared to the distance and distance difference, as shown in Table 4.

Route 1, with a total distance of 3.5 km, and a total collected waste of 77.4 kg, has the optimal index value

TABLE 4. Use case for Intra-grid waste collection for Grid location with small geographical area.

Route	Total Distance	Total Collected Waste	Optimal Index
Route 1	3.4 km	77.4 kg	0.07
Route 2	3.9 km	73.2 kg	0.058
Route 3	3.6 km	69.3 kg	0.072

of 0.07 and thus is considered the second optimal route. Likewise, route 3 has a total distance of 3.9 km, and the total waste collected for this route is 73.2 kg, and therefore, the optimal index value of 0.072 is considered as the third best optimal route.

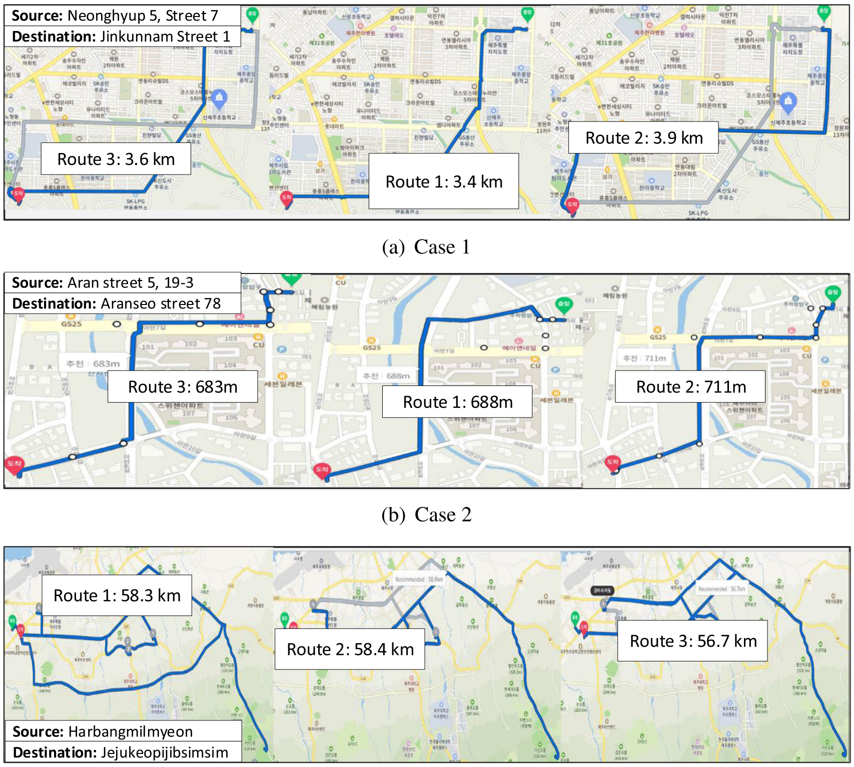
2) CASE 2: INTRA-GRID LONG ROUTES

Some grids are of higher geographical areas, and this specific use case is implemented on those grids which have a relatively higher geographical area. In this case, the initial location is Aran street 5, 19-3, the final location is Aranseo street 78, and the allowed distance is 1 km. The top 3 optimal routes are given in Table 5. Route 2 is the recommended route and is shown in figure 8(a). The optimal route, in this case, is route 2, which has the minimum optimal index because it has more waste compared to the distance and distance difference.

TABLE 5. Use case of Intra-grid waste collection for Grid location with higher geographical area.

Route	Total Distance	Total Collected Waste	Optimal Index
Route 1	0.688 km	12.2 kg	0.023
Route 2	0.711 km	13.5 kg	0.019
Route 3	0.683 km	12.7 kg	0.021

Route 2, with a total distance of 0.771 km, and the total collected waste of 13.5 kg lead to the minimum optimal index of 0.019 and thus taken as the best route. Similarly, route 1 has



(a) Case 1

(b) Case 2

(c) Case 3

FIGURE 8. Use cases.

a total distance of 0.688 km, and the total waste collected of 12.2 kg leads to the optimal index of 0.023 and thus is considered the second-best route. Finally, route 3, with the optimal index value of 0.021 for the total covered a distance of 0.683 km and collected waste of12.7 kg is taken as the third-best route.

3) SPECIAL CASE: ROUTE SPANNING ACROSS MULTIPLE GRIDS

In order to assess the scalability of the system, it has also been tested for routes spanning across different grids. Some vehicles have been assigned more than one grid by the municipality, and hence it is required that the system works equally effective in this case as well. Suppose that the initial location is Harbangmilmyeon, the final location is Jejukeopijibsimsim, the allowed distance is 70 kilometers, and additionally, the truck must cover at least five grids in between the initial and final destination. The top 3 optimal routes are given in Table 6. Route 1 is the recommended route and is shown in Figure 8(a). The optimal route, in this case, is route 1, which has the minimum optimal index because it has the highest waste collection value compared to the distance and distance difference.

Route 3 with a total distance of 56.7 km and the total waste collected of 991 kg leads to the optimal index of 0.77 and is thus considered the second-best route. Likewise, route 2, with a total distance of 58.4 km, and the total collected waste of 873.3 kg lead to the optimal index value of 0.77 and is thus considered the third-best route.

TABLE 6. Use case for Grid location with inter-grid waste collection across a higher geographical area.

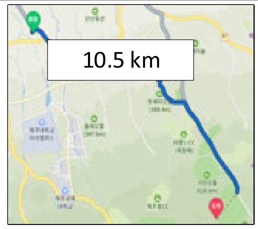
Route	Total Distance	Total Collected Waste	Optimal Index
Route 1	58.3 km	1021 kg	0.66
Route 2	58.4 km	873.3 kg	0.77
Route 3	56.7 km	991 kg	0.76

Apart from these three cases, we have simulated the recommendation system for different grids with different constraints. Some of the cases are listed in table 7, which summarizes the overview of the other cases simulated. As part of the simulation, the initial location, the final location, and the allowed distance are provided by the municipality and based on these constraints; the proposed system suggests the respective topmost optimal routes, which are shown in the rightmost column in table 7.

VII. PERFORMANCE EVALUATION

In this Section, the performance evaluation of PSO, GA, and BAT algorithms has been carried out. The family of algorithms selected for evaluation is considered the best for the combinatorial problem. We have implemented the proposed objective function using these algorithms and evaluated the

TABLE 7. Summary of the use cases for different routes based on the authorities requirements.

Case #	Initial Location	Final Location	Allowed Distance	Route Distance	Total Collected Waste (kg)	Optimal Index	Route
1	Namnyeong-Ro	Sudeok 9 Kil	6	5.2	113	0.03	
2	O-dong 1 kil	Samjo town	7	4.9	125	0.02	
3	Yeongpyeong jikyuhyu meonbil	Jangsang supkil	15	10.5	161	0.29	
4	pyeongjang 2 kil	Samsung Jeonja	10	6.2	102	0.17	
5	komhua	Namsang Ro	10	5.4	119	0.19	
6	Neonghyup 9 Kil	Jin Kun Nam Kil	3	1.5	45	0.05	

performance based on time efficiency and total cost. The time efficiency refers to the time the algorithm takes from the first iteration until the final optimal solution. The total cost corresponds to the cost of the route in terms of fuel consumption and the number of human resources deployed for waste collection. The ideal algorithm would take the minimum amount of time to achieve the lowest cost; however, these algorithms show a tradeoff between time and cost, and therefore, the algorithm which shows the best compromise is chosen in the end. Figure 9 shows the execution time response of different algorithms. PSO is the slowest in terms of execution time, as shown in the bar graph. Nonetheless, this

Algorithm 1 Optimal Route Calculation Based on Proposed Objective Function and rPSO

$InputVariable$

$TotalDistance \leftarrow D_a$

$InitialLocation \leftarrow l_i$

$FinalLocation \leftarrow l_f$

$data \leftarrow dataset$

$ProcessVariable$

$rs \leftarrow allpossibleroute$

$route_c \leftarrow candidateroute$

$\sigma \leftarrow differencebetweenD_aandroutedistance$

$optimalIndex \leftarrow theindexbasedonobjectivefunction$

$OutputVariable$

$optimalRoute \leftarrow RoutewithlowestoptimalIndex$

$rs[] \leftarrow naverAPI(l_i, l_f)$

for $route$ (in) rs **do**

  $dist \leftarrow route.distance$

  if $dist \leq D_a$ **then**

    $route_c[].\sigma[] \leftarrow (D_a - dist)$

    $waste \leftarrow 0$

    for $l \leftarrow route.locations$ **do**

      $features = data[data.loc == l]$

      $waste \leftarrow waste + SVRModel(features)$

    $route_c[].optimalIndex \leftarrow \frac{dist}{waste}\sigma$

$sortedRoutes = Sort(route_c)$

$OptimalRoute = sortedRoutes[0]$

execution time is taken as the best among different trials based on the changes in the parameters of PSO, such as the number of iterations, number of populations, to name a few. GA and BAT solve the optimization functions in a very efficient manner, and the execution time of these algorithms is better than PSO. PSO uses two types of populations, i.e., pbests and current positions. Although this diversity allows greater diversity and exploration over a single population, unlike GA (which with elitism would only be a population of pbests), sometimes due to premature convergence, it takes time to resolve the problem and thus ends up on a slower side. While BAT is the fastest, GA is also very fast as compared to PSO.

The next crucial parameter is the optimal cost it achieves, as the objective of the optimization algorithms is to minimize the total cost. Figure 10 shows the cost comparison of different algorithms, which is the total cost of a vehicle fuel consumption, and the number of human resources needed for the waste collection. In this case, the PSO performs the best among its counterparts. BAT is the second-best, while GA is the least appropriate for this specific scenario. PSO is the best in terms of finding the most optimal solution as it has two dimensions, such as pbest and current solution, and the movement of the particle keeps track of two parameters rather than one in the case of BAT and GA. BAT algorithm is the modern approach of the two, and therefore, it is more focused on finding the optima efficiently.

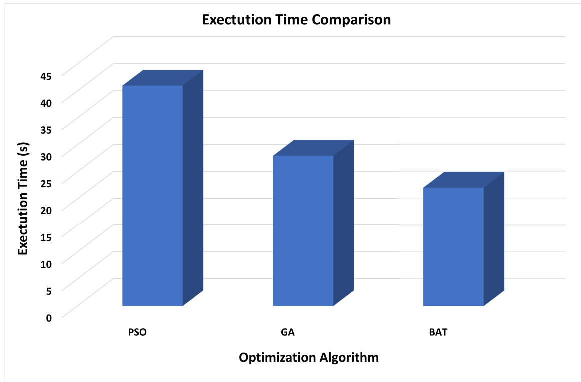


FIGURE 9. Execution time evaluation.

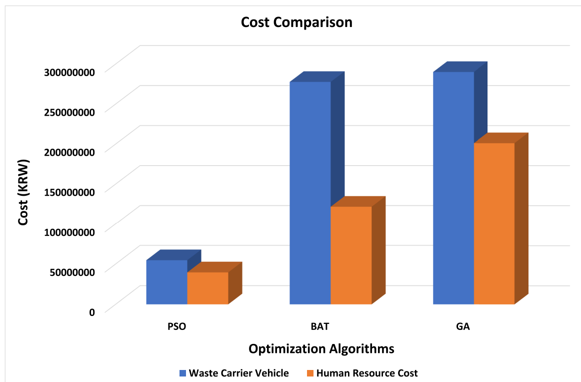


FIGURE 10. Cost evaluation.

PSO is, therefore, best in terms of cost, and BAT is best in terms of execution time. However, the best compromise is PSO as the time difference of PSO is not as huge as compared to the cost difference of PSO with its counterparts. Therefore, it is logical to compromise a little on time to achieve the best cost.

VIII. CONCLUSION

Solid waste management has been considered one of the biggest challenges towards the realization of green and clean projects as part of a smart city transformation of Jeju Island. In this paper, we have proposed an optimal route recommendation system based on the multi-parameter objective function in order to suggest routes that have more waste collection potential and fuel-efficient. We have used a real dataset based on the waste disposal behavior of residential grids. As part of the proposed methodology, we have used the combination of prediction algorithm alongside optimization algorithms to develop a route recommendation system which is not only intelligent but also optimal in terms of fuel-efficiency and time. This recommendation system is beneficial for municipal authorities in terms of resource deployment and planning. Moreover, it is also super-useful for waste carrier vehicle drivers to prioritize the routes which have the potential of bins overflow. The application can also be beneficial for administrators to continually track the status of the grids and schedule waste vehicles out of the schedule in case there is the potential of overflow. The future direction of this work could be the extension of this work to automate the route searching on municipality servers and give notification if there is any route that has overflow or the possibility of overflow. This will be a significant help in the prevention and assurance of a certain level of hygiene in the island. For a tourist hub, suffering from such a huge crisis of waste management challenge, this work is one of the highly needed requirements of the time.

CONFLICT OF INTERESTS

The authors declare that there is no conflict of interests regarding the publication of this paper.

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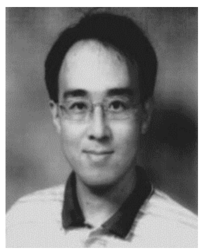

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