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Optimal Policy-Making for Municipal Waste Management Based on Predictive Model Optimization

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ABSTRACT Waste management is an issue of grave concern in the modern urban scenario with the exponentially rising population. Over the past few decades, the Korean government has established several policies to tackle challenges pertaining to solid waste management. To devise a policy, it is necessary to investigate the trends and behaviour of people towards waste disposal. This article fills this gap by proposing a systematic approach of analyzing the solid waste data based on waste profiles of residential grids in Jeju Island. The solid waste data, along with predictive analytics, help the municipality to devise customized policies for different residential grids. We define policy in terms of the number of waste collection human resources cost, waste carrier's vehicle cost and fuel cost. Thus, the paper aims to suggest the number of resources which lead to a minimum cost and also ensure a certain level of hygiene in the area. The analysis is carried out on the solid waste dataset of 2017-2019 generated from different residential grids. The analysis, coupled with prediction algorithms allows the policy-makers to generate a waste profile specific to a residential grid. The optimization algorithm then proposes minimum resources which are enough to ensure hygiene standard of the area based on the waste amount and frequency inside the grid. The results of different areas are illustrated, and the minimum cost is suggested, which enables the policy-makers to not only allocate optimal resources but also helps in ensuring a green and clean environment.

INDEX TERMS Waste management, smart cities transformation, intelligent systems, policy-driven systems.

I. INTRODUCTION

Waste management is an issue of grave concern due to the exponential growth in the amount of waste produced. There has been a linear relationship between economic growth and waste production. This was first quantified by Johnstone *et al.* that a 1% growth in GDP of a country leads to a 0.69% rise in the amount of waste as a result [1], [2]. Considering these linear trends over the recent few decades, waste management has found a focal place in devising sustainable policies and achieving economic goals [3], [4]. Consequently, World bank has recognized solid waste management as of the most demanding areas not only for protecting environment [7] but

also for boosting the economy by intelligent handling of waste disposals and production [11], [12].

One of the challenges in effective waste management is the complexity of current waste management mechanisms. Waste management authorities are interested in coming up with optimal waste management policies to protect the environment from harmful impacts [7]. Some of the principal articles of these policies include proper management of waste such as waste prevention in the first place [8], recycling waste, recovery, and reuse of waste, reducing the cost of waste management operation, disposal of waste [9], [10].

Ineffective waste management operations can lead to many issues [13] such as an increase in the prices of land, strict laws for echo system [14], safety and health issues, ineffective management of waste disposal, limitation of landfill spaces [15], poor waste management policies [16], and the

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less interest of the residents to adopt new technologies [17]. The policy-making for waste management aims to optimize the mechanisms of waste management by embedding the sustainable development concept [18]. Ineffective implementation of waste management policy can lead to a massive impact on the environment, social development, and economy. The core of waste policies depends upon in time waste information generation. In our previous study, we used descriptive and predictive analysis for the in-time waste information generation [19]. Such in-time information is used for policy-making sustainable for the environment. Policy-makers consider more environmentally preferable principles for sustainable policy-making after comparison of various waste management options.

Sustainable policy-making also considers other factors, such as rational use of natural resources, costs minimization hence contributing to the green economy and social development. The challenges for a sustainable solution in a region include its social and economic condition of the area and the possibility of the solution using the available technology [20]. The practical implementation of sustainable policy-making for effective waste management requires finding waste management options, which will accord the conflicts between waste management operations and the environment. Waste management policies should consider strategic plans for waste generation, waste collection, waste separation, waste transport, waste recycling, and disposal [21], [22]. Waste management authorities are in search of reducing waste management operations costs. Moreover, regulations for waste management are concerned about the impacts of waste on the environment [23].

The problem with the approaches mentioned above is the involvement of experts in devising policies. Moreover, a single policy devised across the grids which are applicable for all the geographical area. This approach has a considerable gap for improvements.

Some of the improvements in the current literature are to devise policies which are not generic for all the area but customized for different residential grids because different people have different behaviour for waste disposal. Another improvement could be to offload the expert system and involve machines and sensors, generating a massive volume of data to drive more intelligent solutions [24], [25]. Similarly, the policies devised should not only meet the hygiene requirement of the area but also should be cost-effective. In this article, we address these challenges by proposing customized policies according to the waste disposal trends of residential grids. Similarly, the policy defined is more of a machine-generated than a human expert. The policies suggested are not only intelligent but also optimal in terms of cost. The significant contributions of this article are as follows:

- Provide different analysis of a Waste dataset of Jeju Island to gain insight into the behaviour of grid residents
- Describes optimal policies for efficient cost management based on the predictive analysis and optimization

- Presents the proposed policies on different locations and signifies economic gain.

The dataset used for gaining insight into residential grids is for South Korea, but the applied approach is not limited to local areas. Still, it can be applied to different developing countries. This work will offer significant advantages for developing nations whose economic goals are steep and demands a wiser use of limited financial resources. The proposed work can help the authority to deploy different resources in different locations and thus avoid resource under-utilization.

The rest of the paper is structured as follows. Section II highlights related studies from the literature. Section III describes the methods of the paper and describes the dataset fields and data collection process. Section IV illustrates the approaches which are applied to the dataset to find patterns and extract different waste profiles and discusses prediction results for the upcoming years. Section V discusses the optimization model and the candidate solvers to find the optimal solutions. Section VI presents the results after applying the proposed optimization model and carries out performance evaluation. Finally, Section VII provides the concluding remarks and point out the ideas for future extension of this work.

II. RELATED WORK

Waste management authorities effectively plan waste management operations to reduce the cost of waste management operations and its harmful effect on the environment. Researchers are interested in optimal policy-making for the development of sustainable solutions for waste management. In the literature, many studies focus on waste data analysis for creating solid-waste profiles. The municipality uses these waste profiles as a guideline for the reduction of waste amount generation and resources for waste management operation [22]. Aazam M *et al.* proposed a cloud-based smart mechanism for waste management. The mechanism is based on embedded sensors in the waste bins to notify the level of waste bins. This platform reduces the cost of waste collection operations through optimal estimation of the waste collection route [23]

Guerrero *et al.* carry out a detailed review study of waste management [26], which can help to understand waste management mechanisms better and start brainstorming about waste management operations. The study highlights various activities and phases of waste management systems such as waste collection, waste recycling, waste disposal, waste transportation, and waste classification. The goal of every study was to achieve a near to sustainable solutions for effective waste management.

AI models have also been used extensively in predicting the dynamics of the environment and people towards waste management. BlackBox model such as artificial neural networks (ANN) and kernel-based models such as support vector regression (SVR) is one of the notables [27], [28]. Kernel-based models have been used since 1995; however,

it has not been explored extensively for waste management. The generalizing ability of kernel-based models makes it superior to BlackBox models. Moreover, these models not only have a faster convergence time but also do not suffer from issues such as overfitting and local minima [29], [30]. Nevertheless, there are some instances in which these models are used to make intelligent predictions. For instance, Ravi, Swarnalakshmi *et al.* proposed an intelligent portal based on machine learning algorithms for reliable waste management. The portal work in collaboration with other waste management units such as satellite units for effective management of waste in Smart cities [29].

Similarly, Classification algorithms are also used to categorize waste into various types, such as regular waste, dry waste, wet waste, and hazardous waste. The classified information about waste bins is notified to waste management authorities. Smart waste level notification systems are used to notify the status information of the waste bins to all the stack holders so they can plan waste management. Status information describes the status of the waste bin, such as the level of waste in the bins [32].

Some research studies identify factors that have an impact on waste management operations. Waste generation is proportional to the size of the family, education level, and income of the residents [33]. Waste classification and separation by the inhabitants of the houses are affected by the investment and support of real estate companies and housing societies [34]. Studies show that waste collection and transport practices are affected by ineffective route planning for the garbage trucks, lack of information waste bins level, improper systems for waste bins collection [35], poor road infrastructure, and the number of garbage trucks for waste collection [36]. For the disposal of waste, an electronic system is proposed by Reshmi *et al.* [37]. The system is embedded with various sensors for checking the level of the waste bins and biosensors for detecting harmful waste material. The system uses a GSM module for sending the information to the waste management authorities. The system operates using solar energy to minimize the cost of the operation.

In literature, some studies focused on developing an optimization model for the municipal solid waste system (MSWS). The mixed-integer linear programming model for waste management is proposed in the studies of Mohammadi, M *et al.*, and Santibañez-Aguilar *et al.* They consider waste management as a supply chain problem. The waste supply chain network includes production, distribution, and logistics. Both models maximize waste recycling utilization [38], [39]. The model of Santibañez-Aguilar *et al.* also considers the safety aspect of waste management. A multi-objective model is proposed by Diaz-Barriga-Fernandez *et al.* [40] for the multi-stakeholder problem. The objective of various functions of the models is the maximization of the total net profit in the MSWS. Habibi *et al.* [41] proposed an optimization model for an MSWS considering social development, economy, environment, and to minimize the cost and greenhouse gas emissions.

Similarly, some of the studies discuss policy-making and the challenges of the implementation of waste management policies. Effective waste management policies can lead to social development, economic stability, and environmentally sustainable development [42]. Some studies identify the factors which affect the implementation of waste management policies. For instance, in developing countries, the implementation of waste policies was ineffective due to poor governance and ineffective waste monitoring system [43]. Another factor for the failure of the implementation of waste policies is the lack of commitment among waste management authorities and the stakeholders [44]. Further, in developing countries, waste policy-making neglects the social dimension. The practical implementation of waste management policy can be considered as a political process that is affected by power relations and waste management authorities [45].

Policy-making process in itself has been considered a subjective process and in the hands of human experts. However, the policy-making process should be people-aware and optimized under given consideration. A policy is defined to be cost-effective, and many literature studies are devoted to formulating policies whose goal is to minimize the overall cost [46], [47]. The overall cost is the cost of vehicles, the overall time spent in the waste collection and the fuel cost [48]. There is increasing evidence of the use of solver-based optimization model for solving such logically optimization problems [49]. These solvers are not only fast but also guarantee optimal solutions if handled correctly. However, heuristics algorithms such as particle swarm optimization (PSO) and alike have widely been adopted but their requirements of trials and adjustment plague finding a trustworthy solution [50]. Therefore, we have considered the solver-based approach, which is not only efficient but also precision to find an optimal solution for smart policy.

III. METHODS

In this Section, the methodology of the proposed work is exhibited. The proposed system uses predictive optimization technique first to make an intelligent model and then uses the model alongside constraints to optimize the cost of the policy.

A. DATA COLLECTION

Jeju Island is home to around 695000 citizens living in different residential grids. A residential grid is a territory in which a small community is living. Residents of the same grid share facilities such as convenience stores, community centres, hospitals and waste bins. As part of smart city transformation in 2016, the people behaviour towards waste production is monitored with sensors placed in recycling bins. The data has been collected from the recycle bins located in different grids of Jeju Island. The sensors installed on bin record the time of the waste hit, the amount of waste and other information such as grid ID in which the bin is placed. This information is sent to municipal authorities to collect grid statistics such as population of grid, male and female members, grid

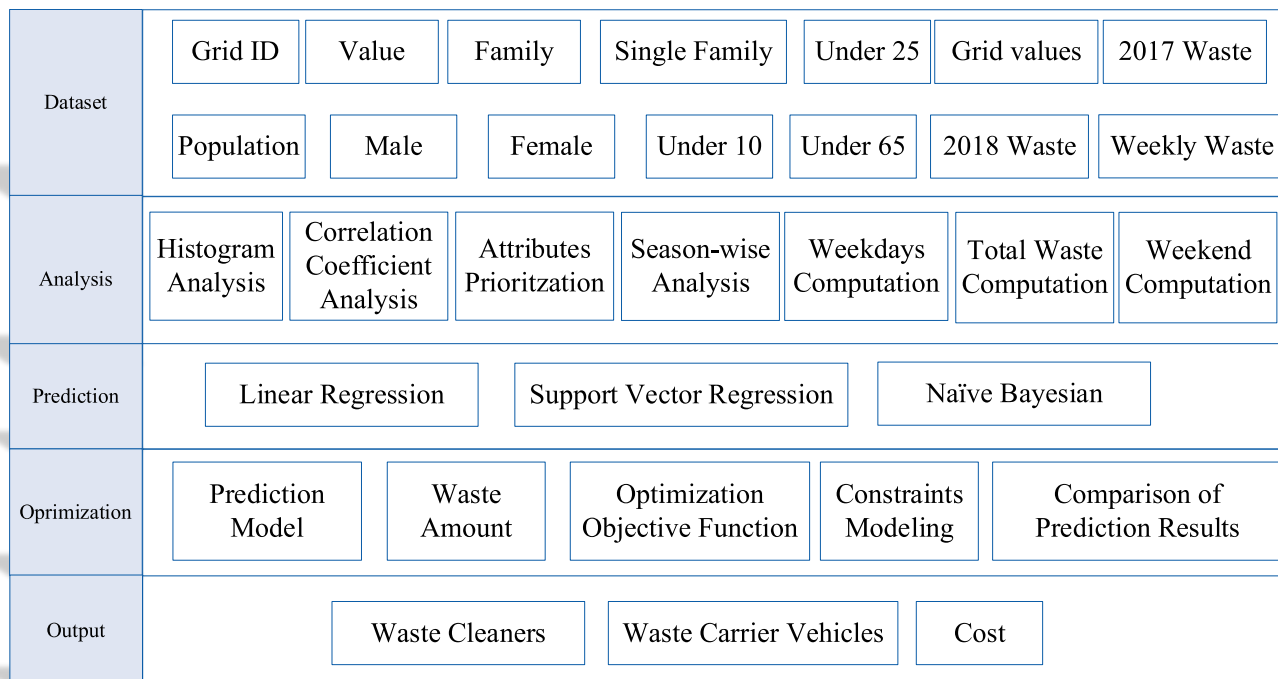


FIGURE 1. Layered system model for waste management.

coordinates, the waste amount for weekdays, and monthly data for 2017 to 2019 in a periodic manner. The dataset for this work consists of 17000 records for 968 distinct grids. The dataset has records of sensors RFID, grid ID and the processed information such as the population of the grid. Furthermore, the population is distributed in certain age groups. These age groups vary from under ten years, 10-25 years, 25-40 years, 40-65 years and over 65 years.

B. SYSTEM MODELING

The proposed system has five different layers; the input dataset layer, analysis layer, prediction layer, optimization layer and output policy layer. Analysis, prediction and optimization layer constitute the process part of the system. The attributes of the input dataset, which are mentioned in the data collection section, are provided to the process part where the data is preprocessed, normalized, and derived fields which are necessary for the waste profile of individual grid is computed and persisted. The output layer considers the profiling of waste based on the processed information from the process layer. It analyses and finds different correlative patterns that can be useful for policy enforcement authorities to devise a policy that suits optimally according to the profile of waste in a specific grid. The correlations among different attributes can be many; for instance, the relationship between population and waste weight, the relationship between particular age group on waste amount can be considered as example use cases.

The output correlation indicates such patterns which have been found with the detailed data analysis. These patterns can help in prioritizing input features for the prediction model.

TABLE 1. Summary of Implementation Stack.

System Component	DESCRIPTION
Operating System	Windows 10, 64 bit
CPU	Intel® Core™ i7-9700K CPU @ 3.60 GHz
Primary Memory	32 GB
Implementation Development Environment (IDE)	PyCharm
Core Programming Language	Python 3.7
Data Analysis Layer	Microsoft Excel, Python Jupyter notebook
Prediction Layer	Scikit Library, Python Jupyter notebook
Optimization	Python Client, Neos Server
Communication API	RESTful API
Solvers	MINOS, KESTREL, CPLEX, IPOPT, PSO

The prediction model alongside input dataset is used to devise an optimal policy which is the use of minimum resources under given constraints.

Figure 1 illustrates the methodology of the proposed work. The data is provided on which preliminary analysis is made. The analysis includes preprocessing, histogram and correlation modelling. The correlation modelling helps in making the prior values to the prediction model.

Secondly, the prediction model is used as a regression model, as the data used is linear and numeric. The constraints and regression model, in turn, helps in finding optimal resources for a given residential grid. The customized policy for every residential grid thus helps in saving financial resources while achieving the same level of hygiene in the area.

C. IMPLEMENTATION STACK

This work is implemented with careful selection of tools and technologies which are open-source and appropriate with the

scope of the work. The dataset is cleaned and analyzed with the combination of Microsoft Excel 2016 and Python-based Jupyter Notebook. The combination of Excel and Python programming language allows the visualization of not only static features but also the derived features as well. The prediction module is implemented with a Python-based Scikitlearn library. Scikit is preferred over other libraries due to the support of various built-in models such as SVR, Naïve Bayesian and Linear Regression. The optimization module is developed with Python client making API calls to NEOS Server, which hosts a variety of A Mathematical Programming Language (AMPL) solvers. This selection is also not random but backed up to undergo a very minimal change to the system if the optimization objective changes and demands a new solver. The selection of AMPL-based solvers is due to its faster convergence time as compared to meta-heuristics algorithms. Table 1 overviews the technology stack used for implementing the proposed system.

IV. ANALYSIS OF DATASET AND PATTERN PROFILING

In this Section, the input data is analyzed, and specific patterns are extracted, which can further pave the way for waste profiling in a particular grid. The dataset contains 54 columns. The data contains grid coordinates, the population inside the grid, male population, female population and different age groups. The waste amount for these attributes is represented in for each across 2017 and 2018. Moreover, day-wise data is also collected for each grid across the same span.

A. DATA PREPROCESSING

There are numerous entries in data where the entities are missed out, causing errors in processing. Specific techniques are there to tackle this challenge; the most common of them is the interpolation. Merely dropping out values are also common if the dataset has massive size. In this work, we ignore the null entries and drop those columns which have missing values. This can be problematic in many cases, but since the data has more than 17000 entries, thus dropping some records will not impact much on the outcome of the results.

Secondly, based on the input attributes, the waste amount is not definite. We computed total waste across 2017 and 2018 for each grid. From the day-wise data, we computed total waste over the weekend and total waste over weekdays. Figure 2 shows the processed field graphical representations. Figure 2 (a) shows the total waste across two years.

Figure 2(b) shows the weekdays and weekend amount. These analyses at this moment do not reflect any useful information in terms of waste profiling. However, in the subsequent sections, it would be made clear that these processed fields play a pivotal role in drawing correlation between different attributes in the dataset and effectively profiling the waste amount based on a particular grid location and population inside the grid.

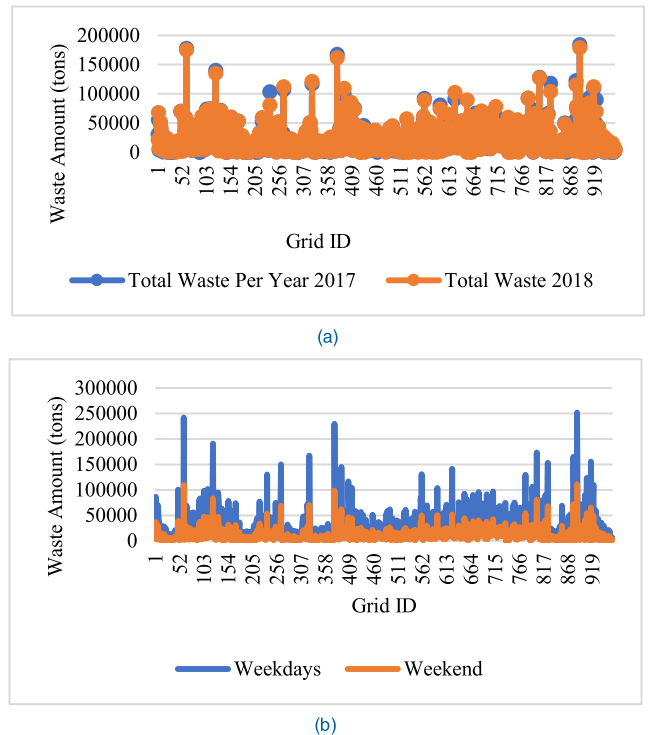


FIGURE 2. Data preprocessing; (a) Total waste across two years, (b) total waste for weekdays vs weekend.

B. CORRELATION ANALYSIS FOR WASTE PROFILING

For effective profiling of waste in a smart city, it is of paramount importance to know the leading factors which have a significant impact on waste amount. In this Section, we analyze different attributes within the dataset and draw their correlation concerning the total waste amount.

It is essential to know the role of male and female within a society in terms of waste disposal. The correlation of gender concerning population shows an index of 0.59 and female as 0.56, which implies that females are less active among the waste frequency. Males are found to have more impact on waste weight which suggests that males more frequently recycles food waste as compared to female.

Another useful information is the day-wise distribution. The correlation between weekdays and the waste amount can help the authorities to schedule special trucks for collection if the forecast for a particular day is high. Sunday and Monday are more frequent in terms of waste production. Saturday has less weight waste produced a day. One of the possible reasons is that people tend to recycle week-long waste either on Sunday night or on Monday morning. In the remaining days, the correlation coefficient is balanced and reflects a constant growth concerning population growth.

The correlation between different age group and waste amount is also highly crucial for waste profiling. Likewise, we are only looking at the count for now, not the individual weight. From Table 2, it is evident that the under age 25 and age 60 senior citizens are the more frequent produced waste persons. This is because under 60 people have relatively more leisure time and has more opportunity to recycle waste. Under

TABLE 2. Correlation of waste amount with different attributes.

TYPE	VALUE	CORRELATION
Day-wise	Mon	0.59762
	Tue	0.589556
	Wed	0.590409
	Thur	0.587938
	Fri	0.584033
	Sat	0.575076
	Sun	0.612645
Gender	Male	0.593369
	Female	0.57143
Age Group	Under 10	0.480765
	Under 25	0.583669
	Under 40	0.474897
	Under 60	0.584078
	Over 60	0.326532
Year-wise	2017	0.606473
	2018	0.570023

25 are the active juniors in the home and are considered the most active participants in waste production.

Finally, the citizens with age less than ten and more than 60 are less relevant to waste amount as per the results. It means these age groups are the least active among the waste production.

C. SEASON-WISE DISTRIBUTION

In this Section, we discuss the distribution of waste in different seasons across 2017 and 2018. Across two years, the season-wise waste amount is computed and is added eventually to find the average waste across two years. Waste distribution is shown in Figure 2. As shown, in the spring season (marked blue), the waste amount is more than other seasons. However, the difference is not subtle. One reason for this slight increase is the campaign carried out in spring for effective waste recycling. For instance, in South Korea, April 4 is observed as a day for green environment. On this day, different campaigns are carried out to recycle waste effectively, and thus people contribute more efforts in recycling. Overall, around 32% of waste is disposed of in the spring season. The next in the list is fall season which contributes 27% overall. The amount of waste in summer and winter is relatively low. Likewise, occasional spikes are also observed for each season due to some special events on a particular day in a calendar year.

D. WASTE AMOUNT PREDICTION

The waste amount for the forthcoming years and the deviation of the waste amount from the previous years are vital for devising a policy for a specific region. The amount of waste determines the resources, and if there is more deviation in the waste, it means the previous policy is not optimally devised. We have computed cumulative waste amount from the dataset for the year 2017, 2018, and 2019. In this work, we consider regression algorithms such as Random Forest, Lasso, Sein-Thel and Support Vector Regressor (SVR) to predict the next year waste amount. SVR algorithm relative performs better. Table 3 summarizes the waste amount for year 2017,2018

TABLE 3. Waste forecasting using SVR algorithm.

ID	2017	2018	2019	2020	Weight (Ton)
1	5465910	7164700	6702290	5759967	25092867
2	5185020	6401820	6215210	5952308.4	23754358.4
3	6471100	7524650	7593361	6333180.4	27922291.4
4	7710590	9339610	6773720	6957774.7	30781694.7
5	6626660	7152160	6749530	6993833.9	27522183.9
6	6167090	7528510	7102180	7084980.8	27882760.8
7	6867220	8179960	7559590	7260173.7	29866943.7
8	6883210	8459190	7550100	7443071.5	30335571.5
9	6320390	8387260	4286550	7582009.4	26576209.4
10	8205560	8048460	6725836.8	7648811	30628667.7
11	6600020	6286680	6725836.8	7457687.8	27070224.6
12	6174830	7171870	6725836.8	7418198.5	27490735.2
Total	78677600	91644870	60532531	83891997	230855001

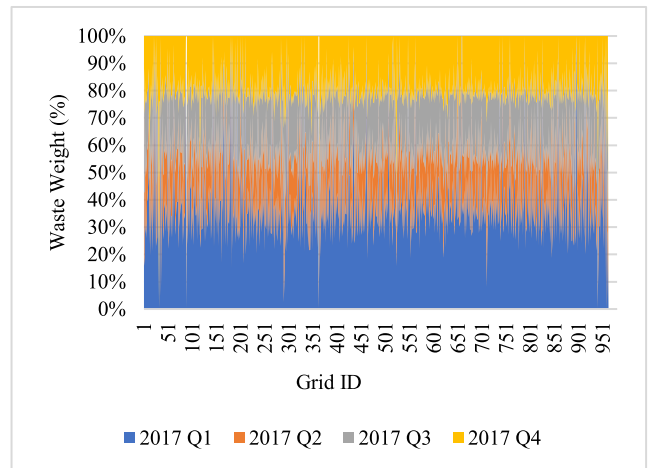


FIGURE 3. Season-wise correlation.

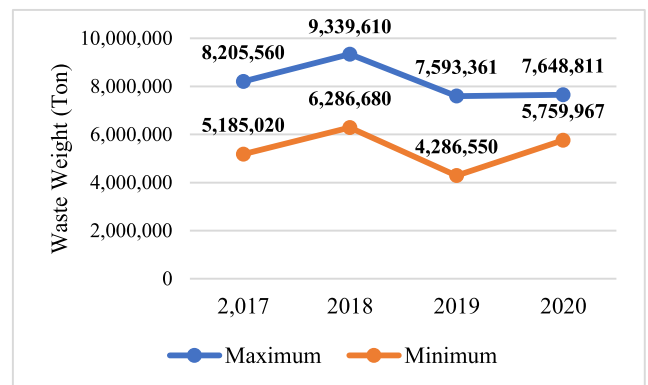


FIGURE 4. Waste deviation across years 2017.01 to 2020.12.

and 2019 and also gives a forecast for next years based on SVR. The next year forecasted waste amount is on the lower side based on the prediction algorithm. The deviation of the waste from the previous year to the next year has been shown in Figure 4. We used statistical measures, such as minimum and maximum, to analyze and investigate the relationship between waste amount ratio of the previous data and expected waste amount. It is found that minimum and maximum values lie between 5,759,967 and 7,648,811 tons.

TABLE 4. Model Evaluators.

EVALUATOR	ACRONYM	FORMULA
Root mean squared error	RMSE	$\sqrt{\frac{1}{n} \sum_{k=0}^n (Y_k - Y'_k)^2}$
Coefficient of Determination	R ²	$1 - \frac{\sum_{k=0}^n (Y_k - Y'_k)^2}{\sum_{k=0}^n (Y_k - \bar{Y})^2}$
Mean Absolute Error	MAE	$\frac{1}{n} \sum_{k=0}^n (Y_k - Y'_k)$
Mean Absolute Percentage Error	MAPE	$\frac{1}{n} \sum_{k=0}^n \left \frac{Y_k - Y'_k}{Y_k} \right $

TABLE 5. Performance Evaluation of SVR with State-of-The-Art Models.

REGRESSION MODELS	RMSE	R2	MAE	MAPE
Lasso Least Angle Regression [52]	66.45	0.61	32.2	31.2
Linear Regression [53]	70.2	0.52	35.2	34.5
Random Forest [54]	67.4	0.59	31.1	30.6
Stochastic Gradient Descent [55]	64.2	0.62	29.1	32.2
Passive-aggressive Regression [56]	73.4	0.52	32.2	40.33
Theil-Sen Regression [57]	72.1	0.54	34.2	36.1
SVR	59.4	0.67	26.4	25.7

E. MODEL EVALUATION

The prediction model is evaluated using statistical measures such as root mean square error (RMSE), mean absolute percentage error (MAPE), mean absolute error (MAE) and Coefficient of determination (R2) which are considered some of the standard model evaluators [51]. In addition to SVR, other regression models have been considered for comparisons. Lasso Regression, Linear Regression, Random Forest and other similar algorithms. Table 4 shows a summary of statistical evaluators and their formulae.

Table 5 summarizes the performance measure of the candidate models for the evaluators in Table 4. It is confirmed that SVR performs better than other models. SVR has the highest R2 value and the lowest error value. The next best model is stochastic gradient descent with a value of 0.62, which is marginally lower than the R2 of SVR. Linear regression performs worst among others with the lowest R2 value of 0.52 and highest mean absolute error 35.2. Nevertheless, passive-aggressive regression is also similar in performance with linear regression.

V. DESIGN OF OPTIMAL POLICY PLANNING SYSTEM FOR SMART WASTE MANAGEMENT

In this Section, the design consideration for devising optimal policy has been illustrated. The policy is based on the predictive analysis of the data. The predictive analysis provides an understanding of the behaviour of citizens towards waste disposal. The number of waste cleaners and waste vehicle carriers depends on the amount of waste forecasted for upcoming years and the deviation observed across recent years. The waste amount defines the number of resources, while the deviation defines the range of upper and lower

limit. The policy devised by the proposed system is also people-aware, and based on the behaviour of people, optimal resources have been allocated. That being said, the policy is intelligent to reflect on the prediction results and deviation results of the residential grids. In the following subsection, the objective function of the optimal policy is derived as a function of the cost of the policy. Thus, the goal is to use minimum resources within the constraints.

A. OBJECTIVE FORMULATION FOR OPTIMAL POLICY

A policy is in the context of this work is the representation of human resources, waste carriers' cost, waste carrier vehicle and total time for waste collection [17], [48]. These parameters contribute to total cost based on the labour cost per hour and the fuel cost of waste carrier vehicle. The objective of the optimal policy is to minimize the cost while ensuring a certain level of hygiene in the grid. The overflow of the waste bins is a risk for the hygiene, and thus part of the policy should be the complete avoidance of overflow.

The integrated cost C, which represents policy is directly proportional to the number of human resources h and number of vehicles v. The cost of human resource is given by (1).

$$C_h = k \sum_{i=1}^h PhC_{hi} \tag{1}$$

where C_h is the cost of a k number of human resource deployed for cleaning, PhC_h is the cost of vehicle per hour. Thus, the total cost is the summation of the total hours the cleaner worked. The cost of waste carrier vehicle is given by (2).

$$C_v = nV_p + \sum_{z=1}^n \left(\int_t^{24} PuC_{f_z} dt \right) \tag{2}$$

where C_v is the cost of an n number of vehicles, V_p is the purchase cost of the vehicle, PuC_{f_z} is the per-unit fuel consumption cost on instance t. The sum of the cost of each vehicle, in turn, is the total fuel consumption on each interval t. The integrated cost C which has to be minimized is given by (3)

$$C = \min w_h C_h^2 + w_v C_v^3 \tag{3}$$

Subjected to the constraint

$$w_h C_h^2 + w_v C_v^3 < 30000000$$

The constraints suggest that the total cost should not exceed 30 million Korean won (Krw) for a single day. In this work, we assume that the cost for a single truck is equivalent to 4 human resources cost. Thus, the value of w_h is set as 0.25 and the value of w_v is set as 1. The number of trucks deployed and the number of cleaners hired is based on the waste profile of the residential.

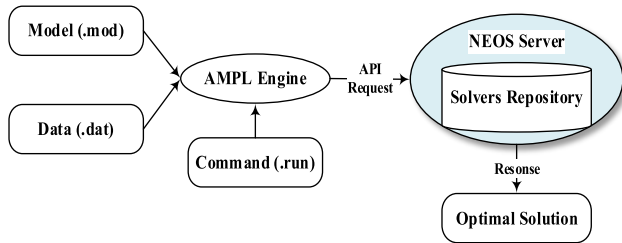


FIGURE 5. AMPL-based optimization flow.

B. A MATHEMATICAL PROGRAMING LANGUAGE (AMPL)

AMPL is an algebraic modelling language to describe and solve complex optimization problems for large-scale mathematical computing. AMPL has built-in support for dozens of open-source and closed-source state-of-the-art solvers. The solvers in most of the cases use mathematical solution rather than heuristics and greedy search mechanisms such as the one used by popular optimization algorithms, i.e., particle swarm optimization (PSO) and genetic algorithm (GA). The mathematical approach for optimization is always faster and solves the given objective function in most scenarios. Therefore, in this article, we used candidate solvers, which are linear and non-linear for the said optimization problem. The popular solvers are CPLEX, FortMP, Minos, KESTREL, Gurubi, IPOPT, SNOPT and LGO. We use CPLEX, IPOPT as linear solvers to solve the non-linear optimization problem. On the contrary, we use KESTREL and MINOS as non-linear solvers to solve a non-linear optimization problem. Figure 5 illustrates the basic working of AMPL-based optimization process.

There are three files; .mod, which is the model file and contains the representation of design parameters, objective function and constraints. Another file is .dat, which contains the data that can be consumed by the optimization solver to find minima or maxima of the given objective function under given constraints. Final file is .run file which specifies the solver to be used, the name of the model file and the name of the data file, the command to solve the objective function and the command to display the final cost function.

VI. RESULTS

In this Section, we discuss the outcome of the experiments. A number of use cases have been simulated to solve the objective function using the above-mentioned candidate solvers. The minimum number of truck and cleaners are computed as an output of the objective function, which is then put in equation (3) to find the final cost.

A. USE CASES

The optimal policy which includes deploying several trucks, cleaners and the estimated cost per day is summarized for every location of Jeju Island. There are two major cities on the island; Jeju city and Seogwipo city. We have taken three different grids from each respective city. Case 1, case2 and case 3 are locations from Jeju city while case 4, case 5 and case 6 are locations based on Seogwipo city.

For case 1, the location is Namnyeong-ro 17, whose total population is 24 person and total waste is 9918.75 tons. The required number of cleaners is three while the required number of trucks is 1. The total per day cost for the cleaning is 88800 Krw. For case 2, the location is O-dong 1 gil, whose total population is 359, and the total waste is 274537.9. The required number of cleaners is 12 while the required number of trucks is 7. The total per day cost for the cleaning is 13218795 Krw. For case 3, the location is Yeongpyeong Gikyuhumeonbil, whose total population is 64, and the total waste is 10912.95 tons. The required number of cleaners is three while the required number of trucks is 1. The total per day cost for the cleaning is 178050 Krw. Case 4, case 5 and case 6 is taken from residential grids of Seogwipo city. The same process is done for those grids locations, and the number of cleaners, trucks and total cost is computed.

Table 6 summarized the use cases of these locations in a tabular form. The results are taken from the best solvers who will be considered in the performance evaluation section. The cost is based on the objective function defined in equation (3) with the suggested weights of 0.25 and 1.

B. PERFORMANCE EVALUATION

The performance of various solvers for the above-mentioned use cases are investigated to assess the significance of the proposed system. As mentioned earlier, we have considered two linear solvers CPLEX, IPOPT, two non-linear solvers MINOS, KESTREL and one heuristic PSO solver. We have calculated evaluation score based on the following equation.

$$E = 0.8C_t + 0.5C_v + 0.3C_h + 0.2S_t$$

where C_t is the total cost, C_v is the cost of the vehicle, C_h is the cost of human resources and S_t is the time taken by the solver to find an optimal solution. High cost and high execution time contribute more to the score, and thus the evaluation score with minimum value is the suggested solution. Similarly, we also defined the deviation of the solution from the ideal score, and the minimum deviation represents the next best solver. Table 7 summarizes the performance measures of the candidate solvers for two grids from each respective cities of Jeju Island. The evaluation score and deviation suggest that the non-linear solvers perform much better than linear solvers. The execution time of non-linear solvers is also reasonably low, which makes them the ideal candidate to solve the proposed objective function. On the contrary, linear solvers such as CPLEX and IPOPT not only guarantee to give a solution but if they do, the score and deviation are much higher and thus it is highly not recommended to use linear solver for such optimization problem. Finally, we also considered PSO as a representative of heuristics family of algorithms. Although it gives a solution in most cases, the optima it achieves is higher than the ones achieved in non-linear solvers such as MINOS and KESTREL. Similarly, the execution time is also very high, which is the case for most of the heuristics and meta-search algorithms. Thus, the performance evaluation suggests

TABLE 6. Optimal policy in terms of cost for different locations of Jeju Island.

LOCATION	POPULATION	TOTAL WASTE (TONS)	CLEANERS	TRUCKS	COST (KRW)
NAMNYEONG-RO 17	24	9918.75	3	1	$z = 0.25x^2 + y^3$
ITER. NO	1		6.2	3.2	1271340
	10		5.2	2.9	934470
	20		4.1	2.5	594825
	30		3.2	2.1	354630
	40		3.2	1.6	199680
	50		2.8	1	88800
O-DONG 1 GIL	359	274537.9	12	7	$z = 0.25x^2 + y^3$
ITER. NO	1		15.7	9.2	9.2
	10		14.2	8.5	8.5
	20		13.9	8.1	8.1
	30		12.2	7.5	7.5
	40		12	7.4	7.4
	50		11.9	7.4	7.4
YEONGPYEONG GIKYUHYUMEONBIL	64	10912.95	12	7	$z = 0.25x^2 + y^3$
ITER. NO	1		15.7	9.2	17847840
	10		14.2	8.5	8617710
	20		13.9	8.1	3146715
	30		12.2	7.5	979290
	40		12	7.4	359505
	50		11.9	7.4	178050
PYENGJEOL 2 GIL	33	14968.2	5	2	$z = 0.25x^2 + y^3$
ITER. NO	1		9.2	4.2	2857440
	10		8.1	4	2412075
	20		7.3	3.2	1382715
	30		6.1	2.9	1010745
	40		5.2	2.1	480630
	50		4.8	2	412800
GUMHWAJEONG YUGSIGDANG	64	59351.25	3	1	$z = 0.25x^2 + y^3$
ITER. NO	1		14.2	8.9	22661370
	10		12.1	7.2	12295515
	20		10.3	5.9	6957045
	30		9.2	5.1	4614330
	40		8.7	4.7	3682365
	50		8.2	3.9	2283870
NOHYEONG 9 GIL	102	80826.85	3	1	$z = 0.25x^2 + y^3$
ITER. NO	1		13.1	7.9	16078245
	10		12.8	7.1	11966130
	20		11.9	6.2	8211915
	30		9.4	5.5	5653950
	40		6.8	3.2	1329840
	50		6.2	2.2	607740

TABLE 7. Performance evaluation of candidate solvers with respect to different parameters.

	PARAMETERS	MINOS	KESTREL	CPLEX	IPOPT	PSO
CASE 1	Total Cost	89910	88800	1271340	1034470	971340
	Vehicle Cost	52131	51221	780232	712212	139121
	Cleaners Cost	37779	37579	491108	322258	832219
	Execution Time	15	21	36	42	37
	Evaluation score	109324.2	107920	1554513	1280351	1096291
	Deviation	1404.2	0	1446593	1172431	1096291
CASE 4	Total Cost	13218795	13236720	N/A	N/A	25209315
	Vehicle Cost	9212118	9121211	N/A	N/A	18212115
	Cleaners Cost	4006677	4115509	N/A	N/A	6997200
	Execution Time	43	34	N/A	N/A	64
	Evaluation score	16383089.5	16384627	N/A	N/A	31372657
	Deviation	0	1537.9	N/A	N/A	14989567

that it is best to use non-linear solvers based on our evaluation criteria.

VII. CONCLUSION

Waste management is a highly challenging issue in the realization of smart cities and ensuring green environment. In developing countries, the resources are limited, thus demand wise use. An optimal policy allows the intelligent use of these resources and avoids over-utilization and under-utilization. In this article, we proposed a policy system for waste management authorities by suggesting a customized optimal policy for every residential grid. The policy is intelligent and optimal and is based on the behaviour of people towards waste disposal amount and frequency. The proposed technique is carried out on a waste dataset from Jeju Island. The patterns found in each grid has contributed towards predicting the number of resources. At the same time, the proposed objective function uses the prediction results to find the optimal and cost-efficient solution. Such methods seem trivial for developed nations, but countries which have limited resources, such wise use of resources can save a considerable amount of resources which can be utilized in other development areas. Moreover, the timely collection of waste and avoidance of waste overflow can also contribute towards the environment. This work can be extended in future by automatically learning the optimal policy without the need for predictive analysis and massive sets.

AUTHOR CONTRIBUTIONS

Shabir Ahmad conceived the idea, designed the experiments and wrote the original draft. Imran assisted in prediction modeling and comparisons. Naeem Iqbal and Faisal Jamil assisted in data preprocessing. DoHyeun Kim conceived the idea and supervised this work.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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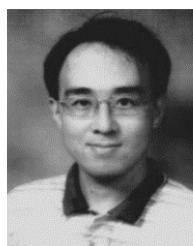


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