Original article

AI Techniques Aid for Optimizing the Collection System of Industrial Plastic Waste

Richao CONG†, Atsushi FUJIYAMA and Toru MATSUMOTO

Abstract

Instead of statistical approaches, artificial intelligence (AI) techniques have been utilized for waste management in many fields owing to their higher accuracy. It provides opportunities to make accurate future predictions of collection demands and detect the optimal collection routes. This study aims to address plastic waste management using AI by applying predicted individual collection demands of industrial plastic waste (IPW) to an integrated collection system, as demonstrated in the Fukuoka Prefecture, Japan.

We propose an AI-based approach for applying known collection demands of IPW regarding vehicle routing problems to better integrate the existing IPW collection system. After providing details on future prediction of the collection demands through the machine learning approach, the Euclidean-distance-optimized vehicle routing problem was solved using Python. To further validate this method, an optimal route was estimated for a real road network. Finally, reductions in traveling distance and carbon dioxide (CO_2) emissions were evaluated for the collection system both before and after AI-assisted integration.

In this study, a distance-optimized collection route was identified, thus demonstrating the feasibility of integrating existing collection systems using AI technology. This integration was proven to be beneficial in terms of the traveling distance (22 km reduced per collection, *i.e.*, 14.2% of the total distance was reduced) and CO_2 emissions (4.8 kg-CO_2 reduced per collection, *i.e.*, 10.1% of the total emissions were reduced).

Key Words: AI technology, industrial plastic waste, machine learning, system optimization, vehicle routing problem

1. Introduction

Japan has emphasized effective recycling of plastic waste (PW) since an embargo on the import of PW, issued by the Chinese government in July 2017[1)]. The total amount of PW generated by Japan in 2017 was approximately 863 million tonnes, of which industrial PW (IPW) accounted for 54%[2)]. Understanding the collection potential of IPW in any locality is meaningful for optimizing its recycling system *e.g.*, collection and disposal schedules, vehicle deployment, and personnel arrangements. Thus, there is a need for models that enable the accurate prediction of this collection potential.

Previous studies have applied a variety of statistical models, such as multiple linear regression models[3, 4)], vector autoregressions[5)], and seasonal autoregressive integrated moving averages[6, 7)], to predict future problems. In recent years, artificial intelligence (AI) technologies have been used increasingly often for analyzing complex "big data," due to their higher prediction accuracy in many fields[8–10)]. For waste

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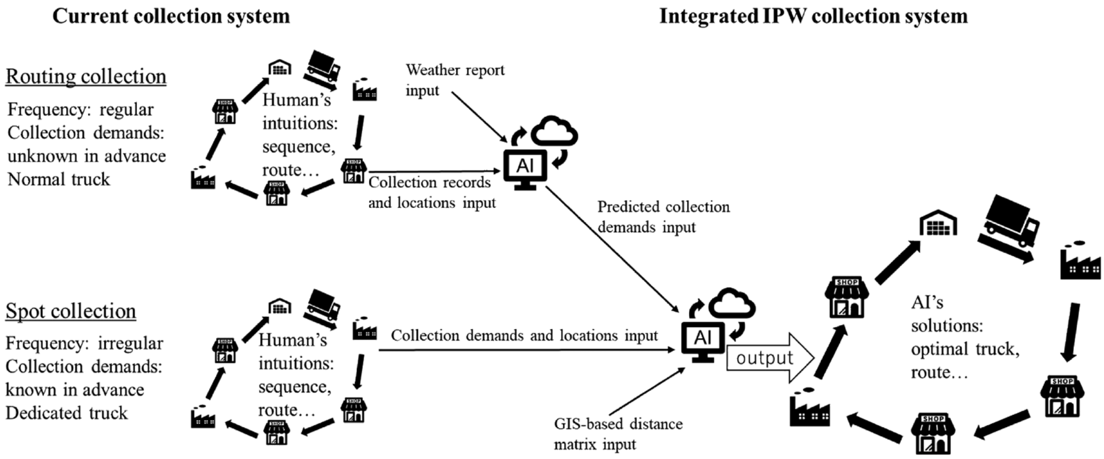


Fig. 1 A proposed system on integrating the current industrial plastic waste (IPW) collection system by AI technique

management, both single and multiple models have been developed to forecast the generation of municipal solid waste (MSW)[11, 12], and to solve optimization problems regarding the cost of waste collection and subsequent transportation[13]. In Japan, Cong *et al.* developed a machine learning approach with 28 models on future predictions of daily IPW collection demands from a supermarket in Fukuoka. A higher prediction accuracy (seven days mean) is achieved by the selected fitting model (optimal ensemble model: 93.6%) than that by a statistical approach (linear regression tool of SPSS: 83.1%)[14]; however, a demonstration of the use of the predicted IPW collection demand has not been conducted.

Routing collections of IPW (*i.e.*, regular collection) coexist with spot collections (irregular) in the current collection system of Japan. As reported by Cong *et al.*[14], problems within this system include certain collection points (*i.e.*, facilities) being visited even when there is only 1 kg of IPW to collect, and some collection points are being visited more than once per day; thus, different trucks had to be prepared for two types of collections. Owing to the long-term accumulation of collection records from routing collection facilities, it is possible to accurately predict their collection demands using AI technology. This provides an opportunity to integrate these two types of collections towards solving a vehicle routing problem (VRP)[15].

Previous studies have used geographic information systems (GIS) to solve the VRPs for MSW collection[16, 17] and for household PW collection[18]. AI techniques have also been used for VRPs in MSW studies[19–21]. In this study, the AI-GIS combined approach was explored to search for the optimal solution for the VRP on IPW collection.

The aims of this study were as follows: 1) to propose an AI-based system for integrating routing collections with spot collections; 2) search for an optimal collection route by using previously known collection demands; 3) validate the optimal solution using a real road network; 4) and evaluate the CO_2 emission reductions from the collections before and after the optimization.

2. Methods

2.1 *Description of the proposed system*

Based on the information from the existing collection system, which was obtained from the local recycling company, a framework for integrating the current system was proposed, as shown in Fig. 1. The AI techniques used in this study include the machine learning approach on future predictions of collection demands and application of optimization for vehicle routing problems. Like with the prediction accuracy demonstrated by Cong *et al.*[14], the predicted collection demands from the routing collection targets are sufficiently accurate for use in integrating the two aforementioned types of collections. First, the daily collection demands for routing collection facilities are accurately predicted by the AI based on the accumulated "big data" (*i.e.*, collection records). Following this, a distance-optimized collection route is detected by the AI to integrate the routing collection and spot collection facilities.

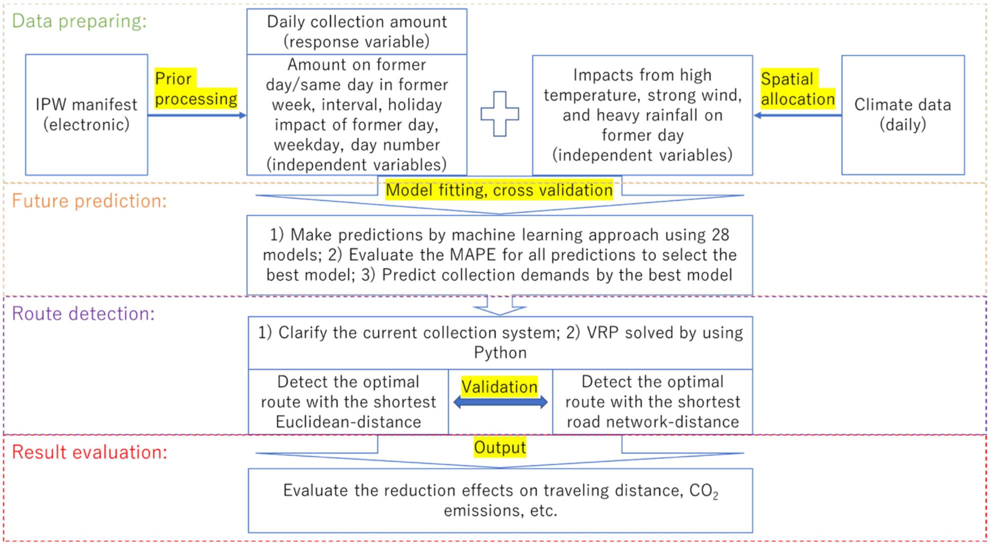


Fig. 2 Workflow used to predict the industrial plastic waste (IPW) collection amount for integrating the current collection system by AI technique

2.2 *The work flow and data preparation*

Fig. 2 shows the workflow that has been used to predict the amount of IPW collected from individual facilities, to be used for integrating the current collection system using AI. We first processed the waste manifest data and combined these with daily weather data. The data was fitted to all 28 models which were stored in a regression learner application in MATLAB R2021a. We then evaluated their accuracy based on the predicted results, in order to select the best model for predicting the collection demands. Subsequently, a VRP was designed to integrate the routing collections with the spot collections, and a distance-optimized (*i.e.*, Euclidean-distance) route was searched using an optimal tool established in Python 3.0; for validation purposes, another optimal route was detected based on the road network. Finally, we evaluated changes in the traveling distance and CO_2 emissions in the collection system both before and after optimization.

The IPW collection amounts were referred to the waste manifest data, obtained from a local recycling company in the Fukuoka Prefecture. These data included daily collection records on the amount of IPW collected at the facility level from April 2018 to September 2020 and covered multiple sectors. Climate data from daily weather reports[22] were also used in this study, which may have affected the IPW collections. The road network used for routing validation was a commercial database of digital road maps[23].

2.3 *The collection demands prediction by machine learning*

Initial sense on future predictions of this study was referred to a previous study[14]. Unlike that study, we excluded variable selection and chose the best model in the final prediction stage by comparing their mean absolute percentage error (MAPE)[24] based on all tested results rather than the root mean square error (RMSE)[25]. The steps for future predictions are shown as follows:

First, to ensure prediction accuracy, we prepared seven independent variables (see descriptions on Table 1) besides the response variable (daily amount collected) for each collection day (total records: 912 days). Second, for validation purpose, we split the whole dataset into training data (collection days before September 2020; 96.8% of data number) and test data (collection days in September 2020; 3.2%). Third, we processed the training data with data smoothing and outlier embedding. Fourth, we performed five-cross-validation through model fitting by 28 models (see Table 2) for training data and made predictions by the fitted models for test data. Fifth, MAPEs of all predictions were calculated for test data as validations based on the predicted and the observed values. Sixth, the model with the lowest MAPE was selected as the best one (the highest accuracy) and used for future predictions.

2.4 *The current condition on IPW collections and the optimal collection-route detection by Python*

Owing to data limitations, we used real records of IPW collection amounts on August 1, 2021, instead of the future predicted values for collection-route optimization. To decipher the existing collection system, we relied on the real collection sequence and the amount of IPW collected by routing collections and spot collections on August 1, 2021, from the same company. The coordinates of the related facilities were collected using Google Maps[26]. To maintain anonymity for local companies, their locations are shown without these coordinates. The real case including a routing collection (*i.e.*, red lines on the left) and a spot collection (*i.e.*, green lines on the right) on August 1, 2021 is shown in Fig. 3. The numbers in purple near these points (from small to large) show the sequence of collection, and the blue point shows

Table 1 Description of the independent variables used in this study

Variable	Description
Day_num	day number from 2018.4.1 to 2020.9.30
Weekday	category type on what day it was the day
Pre_d_climate	category type on climate impact of previous day: wind speed >=$10\,\mathrm{m\,s^{-1}}$, daily rainfall >=20 mm, highest temperature >=35 degree
Pre_d_holiday	category type on previous day belongs to holiday or not
Interval	the interval between the present and former collection day
Num_fday	the amount on former collection day
Num_ sday_fw	the amount on the same day of the former week

Table 2 The description of the fitted 28 models which were stored in a regression learner application in MATLAB R2021a

Description by regression model type	Model used
Linear Regression Models have predictors that are linear in the model parameters, are easy to interpret, and fast for making predictions. The accuracy is often low due to the constrained form	Linear Regression
	Interactions Linear
	Robust Linear
	Stepwise Linear
Regression Trees are easy to interpret, fast for fitting and prediction, and low on memory usage. Control the leaf size could prevent overfitting	Fine Tree
	Medium Tree
	Coarse Tree
SVM: Linear SVMs are easy to interpret, but can have low predictive accuracy. Nonlinear SVMs are more difficult to interpret, but can be more accurate with options on Kernel function, standardize, box constraint, Epsilon, and Kernel scale modes	Linear SVM
	Quadratic SVM
	Cubic SVM
	Fine Gaussian SVM
	Medium Gaussian SVM
	Coarse Gaussian SVM
Ensemble of Trees models combine results from many weak learners into one good ensemble model	Boosted Trees
	Bagged Trees
Gaussian Process Regression (GPR) models: GPR models are often highly accurate, but can be difficult to interpret. Like with nonlinear SVMs, there are many advanced options for model control	Rational Quadratic
	Squared Exponential
	Matern 5/2
	Exponential
Neural Networks: Neural network models typically have good predictive accuracy; however, they are not easy to interpret. Model flexibility increases with the size and number of fully connected layers in the neural network	Narrow Neural Network
	Medium Neural Network
	Wide Neural Network
	Bilayered Neural Network
	Trilayered Neural Network
Optimizable models: Different combinations of hyperparameter values are tried automatically by using an optimization scheme to seek the optimized hyperparameters for minimum mean squared error	Optimizable Tree
	Optimizable SVM
	Optimizable GPR
	Optimizable Ensemble

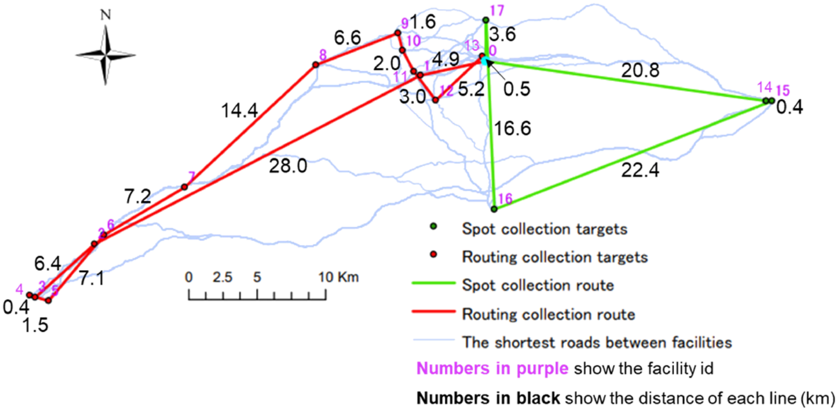


Fig. 3 The real case on routing collections and spot collections of IPW on August 1, 2021 by two trucks from a local recycling company in Fukuoka. The blue point with a number zero shows the location of the recycling company

Table 3 Parameter setting for evaluation on CO_2 emissions

Term	Value	Unit
Collection sequence	given by Python	—
Accumulated load of truck	given by Python	t
Traveling distance of each link	given by GIS	km
Loading rate of truck (less than 10%)	10	%
Loading rate of truck (more than 10%)	counted as the accumulated load	%
Emission factor of diesel fuel	2.62[30]	$kg\,CO_2\,l^{-1}$
Emission factor for empty truck	0.315[31]	$kg\,CO_2\,km^{-1}$

the starting point of the collection (*i.e.*, the location of the recycling company).

An integrated collection system was assumed to be collected from the 17 facilities in Fig. 3 in one route by one truck whose collection demands were known previously. To solve the VRP, an objective function on the traveling distance and constraint by truck in collections were defined as:

$$Min \sum_{k \in K} \sum_{(i,j) \in E} d_{ij} x_{ij} \tag{1}$$

which is subject to:

$$\sum_{i \in V} \sum_{j \in V \setminus 0, i \neq j} q_j x_{ij} \leq Q \tag{2}$$

where, Equation 1 shows the objective function for the minimum total travel distance, d_{ij} is the distance between facilities i and j (km), x_{ij} is the binary variable showing whether the truck passes the route between facility i and j or not; Equation 2 provides the constraint values that the total load of truck collecting from the facilities q_j (t) should not exceed its capacity Q. Based on the total amount of IPW in the real-life scenario, a 2-t commercial truck was assumed to be used in the collections (Q=2).

The OR-tools[27] developed by Google were installed in Python to search for the optimal route. The metaheuristic uses OR tools, which is a higher-level procedure designed to find, generate, or select a heuristic to provide a sufficiently good solution to an optimization problem[28]. The distance matrices on the Euclidean distance and road network distance between these facilities were generated using GIS software. Based on the coordinates of all facilities, their locations were mapped as points; the links (*i.e.*, lines) between each pair of point groups were generated using GIS tools[18, 29]. Distance matrices were then read from the length of the related lines (*i.e.*, links) and used for the VRP in Python.

After this resolution, the optimized collection route was detected, and the CO_2 emissions were calculated using the parameters listed in Table 3. Based on the loading rates and accumulated ton-kilometers values, the evaluation was made by an improved ton-kilometer method[30]. For processes with a loading rate of less than 10%, an emission factor of the empty truck was utilized in the calculations[31].

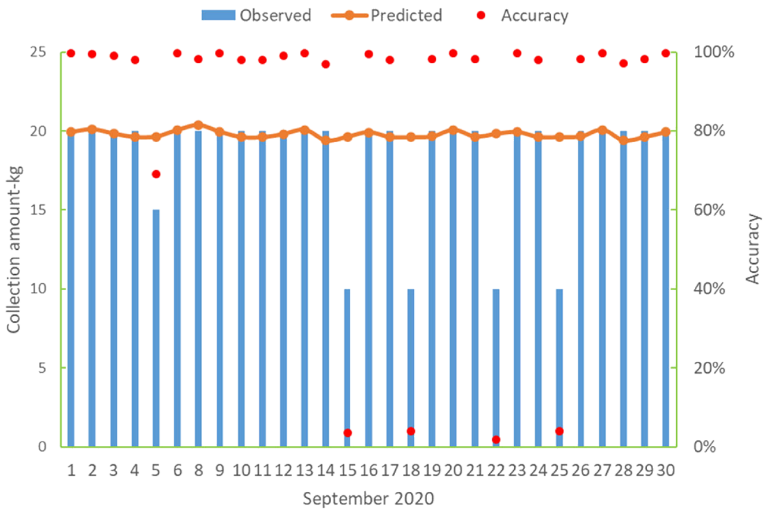


Fig. 4 The predicted and observed values on daily IPW collection amount (kg) in September 2020 (no collection was recorded on September 7) and the accuracy (refer to right y-axis) between them

3. Results and discussion

3.1 Predicted collection demands

By evaluating the prediction accuracies for all models, the best model for a supermarket belonging to routing collection was the coarse Gaussian-supported vector machine model (with a monthly mean accuracy of 84.6%). As shown in Fig. 4, the values predicted by the best model (*i.e.*, orange lines) appear to be smoother than the observed values (*i.e.*, blue bars). We found that daily prediction accuracies were stable for the first two weeks (with a mean accuracy of 96.5%; *i.e.*, a stable prediction period) from September 1, 2020. It also reflects the fact that the collection demands predicted by this approach are sufficiently accurate and the stable prediction period is long enough to be used for solving the real problems. On the other hand, those days with extremely low prediction accuracies showed that the prediction accuracy dropped on some days. The trend learned by the model made the predicted values slightly vary around 20 kg so that significant errors would occur once the observed values were far from 20. In other words, the amount of 10 kg in training data occurred out of order (*e.g.*, an observed interval for a period without the occurrence of 10 was up to 57 days), resulting in the fitted model lacking accuracy in predicting this value (*i.e.*, collections on 15th, 18th, 22nd, 25th).

3.2 The detected optimal collection routes and evaluations on the optimization

Based on the collection demands from the real-life scenario (Fig. 3), the distance-optimized routes from the 17 facilities in Fukuoka were detected using Python, as shown in Fig. 5. The total traveling Euclidean distance of the optimized 1-route case was approximately 131 km (Fig. 5A) and that of the road network case was approximately 154 km (Fig. 5B). Assuming the working time is 8 hours per day, the needed average traveling speed of a truck in one collection route is estimated at about 20 km h^{-1} which reflects that it is possible to go through all facilities in one day. During our validation process, the collection sequences in the two optimized routes were almost the same (where collections from facility id 5-4-3-2 in Fig. 5A but 5-3-4-2 in Fig. 5B), which indicates that this Euclidean distance-based approach is reasonable to some content for use in future applications. Meanwhile, if road network data is available, it is suggested to be used to solve the real VRPs for higher accuracy.

The traveling distance (Euclidean distance) was found to be reduced by the optimization and CO_2 emissions were evaluated based on the real collection amounts, as shown in Fig. 6. Compared to the real-life scenario (total distance: 153 km), there was a traveling distance of approximately 22 km (*i.e.*, 14.2% of the total in the real-life scenario) reduced after the optimization (Fig. 6A). Through this in-

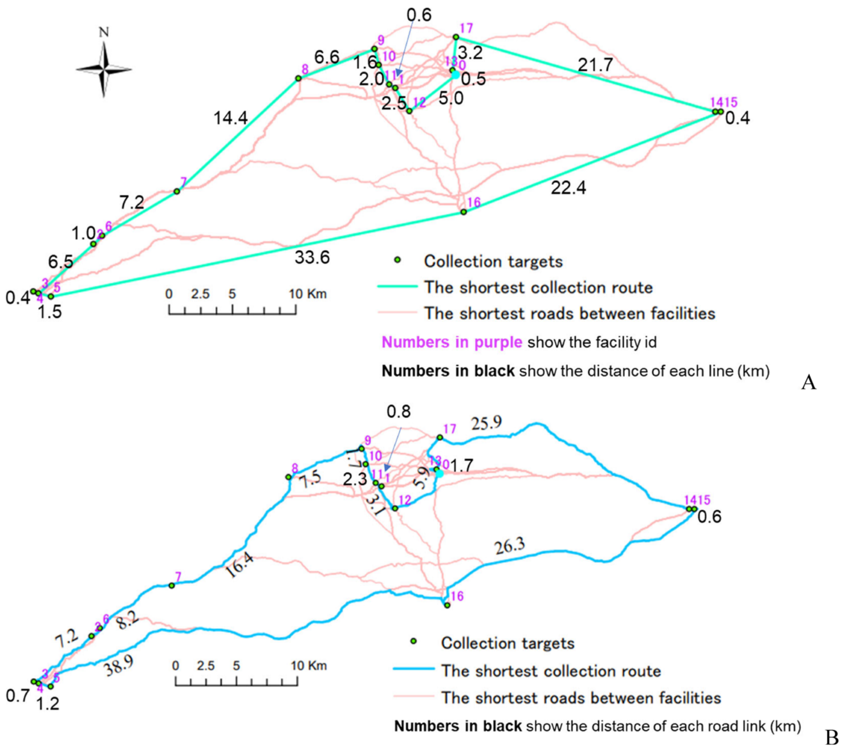


Fig. 5 The shortest routes on IPW collections on: (A) Euclidean-distance optimized; (B) road network-distance optimized

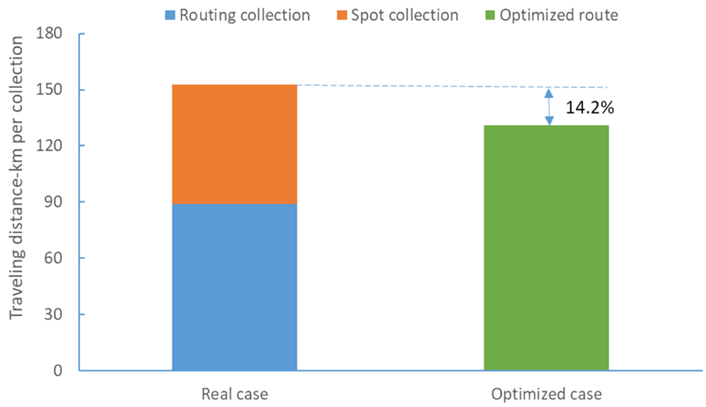
tegration, one truck and many traveling distances were saved, which is meaningful for local recycling companies. The reduction in CO_2 emissions was estimated to be approximately 4.8 kg-CO_2 per collection (*i.e.*, 10.1% of the total emissions in the real scenario). This implies that the optimization effect is large; therefore, integrating the current collection system is important not only for cost saving but also for carbon mitigation.

However, to construct such an integrated collection system, "big data" on routing collection facilities is required to support accurate future predictions using AI technology. Moreover, an advanced technique for data processing and AI applications is essential. On the other hands, the accuracy of future predictions is limited by the accuracy of the data used, for example, the predicted climate data for future days.

4. Conclusions

In this study, we proposed an integrated IPW collection system to link the future prediction of collection demands from routing collection facilities with spot collection ones for VRP solving using the AI technique. The best prediction model for a supermarket was found using a coarse Gaussian-supported vector machine model (with a monthly mean accuracy of 84.6%) and the stable prediction period was two weeks from September 1, 2020. Moreover, the total-traveling-distance-optimized routes were detected using the Euclidean distance and road network distance. The results of routing validation showed that this AI-based approach is reasonable for use in such applications. Finally, the benefit from this integration was proven through the traveling distance (*i.e.*, 22 km reduction, which is 14.2% of the total) and CO_2 emissions (*i.e.*, 4.8 kg-CO_2 reduction, which is 10.1% of the total). This demonstrates the high potential for integrating this method in the environmental aspect.

Once the collection records are available until August 2021, we suggest that the predicted collection demands made by this AI technique are used for solving the VRP. As a next step, a real-time optimized collection system and further variables for better prediction accuracy should be explored. The evaluations on the system optimization from economic aspect will be considered in future work.



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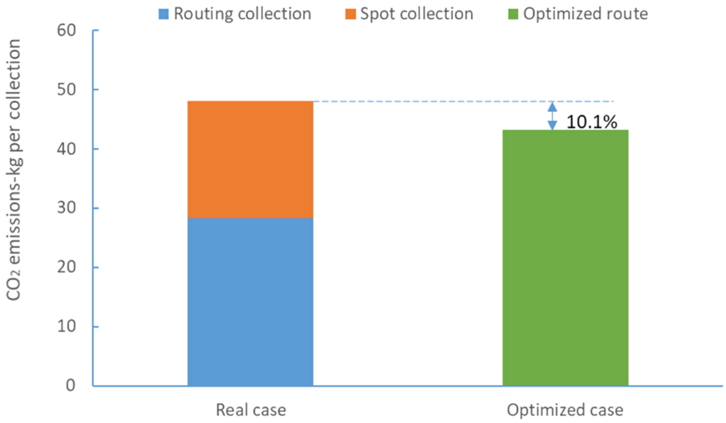

B

Fig. 6 The comparisons between the rea case and the optimized case of IPW collections from 17 facilities on: A) traveling distance; B) CO_2 emissions

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AI技術による産業系廃プラスチック回収システムの統合化

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摘　　要

既存の統計手法と比較して，より精度の高いAI技術が多くの分野で応用されるようになった。これにより，回収需要量の予測の他，収集運搬のルート最適化（巡回の順番やルート，配車等）が可能となる可能性がある。本研究の目的は，AI技術を用いることで，福岡県における産業系廃プラスチックを対象に，回収需要量予測とルート最適化を統合化させ，それによる効率化を目指すことである。

本研究では，AI技術を用いて廃プラの1日当たり回収需要量の推計結果を輸送計画問題に適用することによって，従来の回収システムを統合化することを提案した。まず，機械学習による将来予測手法を提示した上で，Pythonを用いて総移動距離（直線距離）の最小化に関する輸送計画問題を解いた。さらに，結果を検証するために，道路網に基づいた最適なルートを検出した。最後に，システムの統合前後による総移動距離やCO_2排出量の変化を評価した。

総移動距離の最適な回収ルートを検出したことによって，システム統合の有効性を示した。具体的には，総移動距離（回収1回当たりの削減：22 km, 14.2%）及び二酸化炭素排出量（回収1回当たりの削減：4.8 kg-CO_2，10.1%）の削減があることを確認した。

キーワード：AI技術，産業系廃プラスチック，機械学習，システム最適化，輸送計画問題