〔原著論文：審査付〕

Collection of Industrial Plastic Waste During the COVID-19 Pandemic: A Case Study of the Wholesale and Retail Trade Sector in Fukuoka Prefecture, Japan

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Abstract: Fukuoka Prefecture, Japan, has been heavily affected by COVID-19. Since the first patient reported in February 2020, the total case count has risen to 34,937 as of June 12, 2021. However, the effects of these conditions on industrial plastic waste (IPW) collection and their implications for future trends in this area are still not clear. This study statistically analyzed monthly collection trends and geographic variations in the total amount of IPW collected in Fukuoka Prefecture based on daily waste manifest data from a local company. We found the total amount of IPW collected decreased significantly in April and May 2020 corresponding to a state of emergency. Meanwhile, a fact was confirmed that not all facilities were affected by it. Furthermore, multiple linear regression analysis confirmed that the amount of IPW collected monthly from the wholesale and retail trade sector was strongly correlated ($R^2 = 0.94$) with both the amount of sales in that sector and the number of patients with COVID-19. Finally, we developed a machine learning approach to future prediction with regard to the amount of IPW to be collected from individual facilities. We confirmed that future predictions made by machine learning had higher accuracy (93.6%) than those made using a statistical approach (83.1%). This study demonstrates that waste manifest data are useful not only for illuminating trends in IPW collection but also for making future predictions regarding the amount of IPW to be collected.
Keywords: *Artificial Intelligence, future prediction, industrial plastic waste, machine learning, waste manifest*

1. Introduction

In 2017, the total amount of plastic waste (PW) generated in Japan was reported to be approximately 863 million tonnes, of which industrial PW (IPW) accounted for 54%[1]. In July 2017, the Chinese government issued an embargo on importation of PW[2]; since then, Japan has emphasized on the effective recycling of PW. At the end of 2019, the COVID-19 pandemic began, resulting in serious impacts on normal human activity, including the IPW recycling industry. For instance, the increased working-at-home days would reduce the plastic loss from manufacturing factories and the decreased outdoor activities would also reduce the packing-use of IPW generated from hotels, restaurants, and public-use facilities. The decreasing generation could affect the amount of IPW to be collected and recycled. A clear understanding of PW collection status and potential in a locality is key to optimize the recycling system, particularly with regard to collection and disposal schedules, vehicle deployment, and personnel arrangements. Thus, there is a need for models that enable immediate assessment of collection status and accurate prediction of collection potential.

To accurately capture the current trend of IPW collection at a prefecture-level especially during the COVID-19 pandemic, at least monthly statistical data is needed. Since the desired data is not available, the electronic waste manifest data at a daily level from a local recycling company is used here to solve that problem. Previous studies have applied a variety of statistical models, such as linear regression and multiple linear regression models, vector autoregression (VAR), and seasonal autoregressive integrated moving average (SARIMA), for future-prediction problems. In recent years, artificial intelligence (AI) techniques for analyzing "big data" have increasingly been utilized for future-prediction problems, as they provide higher accuracy in many fields e.g., mental healthcare[3)], waste generation[4)], and soil temperature prediction[5)].

Noori et al. (2009) developed an improved support-vector machine (SVM) model and combined it with principal component analysis to forecast weekly generation of municipal solid waste (MSW) in the city of Mashhad, Iran[6)]. In Japan, Takahashi et al. (2011) developed a simple inundation prediction system based on training an SVM using past inundation and rainfall records for Tokyo[7)]. Shamshiry et al. (2014) combined an artificial neural network (ANN)–genetic algorithm model with the response surface method to predict MSW generation in Langkawi Island, Malaysia, with the purpose of optimizing the cost of waste collection and transportation[8)]. Liu et al. (2018) used Gaussian process regression and multiple imputations to predict wind power with missing data in Jiangsu, China[9)]. Kannangara et al. (2018) applied ANN and decision tree algorithms to predict MSW in Ontario, Canada, using socio-economic and demographic parameters[10)]. Montecinos et al. (2018) proposed a forecast model based on Theil–Sen constrained regression for the daily oil waste of several agro-food industry sites in North America and compared their result with a linear regression model[11)]. Shibata et al. (2019) explored the effect of changes in ANN model configuration when predicting next-day hourly electric demand in the Chubu region of Japan[12)]. Tamaya and Kakuichi (2020) predicted the appropriate timing of vascular access intervention therapy using random forest, gradient boost, decision tree, and logistic regression algorithms[13)]. However, we found no previous studies on the use of AI techniques to predict future IPW generation.

In light of this background, the aims of the present study were as follows: 1) clarify the current status of IPW collection system in Fukuoka Prefecture based on waste manifest data, especially with regard to the effects of the COVID-19 pandemic; 2) explore the correlation between the amount collected and various socio-economic factors focusing on the wholesale and retail trade sector; and 3) make predictions of future IPW generation using AI techniques and statistical approaches to predict them at the individual facility level and sector level in different timescales.

2. Methodology

2-1 Study Area and Problems of the Current IPW Collection System

In Japan, Fukuoka Prefecture has a large number of patients infected with COVID-19, with 34,937 SARS-CoV-2-positive people having been reported as of June 12, 2021[14)]. Using daily waste manifest data from a local recycling company (collected from April 2018 to September 2020), we analyzed the conditions of IPW collection in Fukuoka Prefecture. Soft vinyl waste was collected and compressed as cube plastic fuel by this company. Several problems were found in the collection system, which are as follows: 1) the collection routes were normally determined by the drivers; 2) some collection points (facilities) were visited even when there was only

1 kg of IPW to collect; 3) some collection points were visited more than once in a day; 4) some collection points had to transport their IPW by themselves; and 5) the collection frequency was inconsistent at most points. These points indicate that the current collection system is inefficient and needs to be improved. If the individual collection demand is predicted accurately, problems 2) and 3) would be controlled.

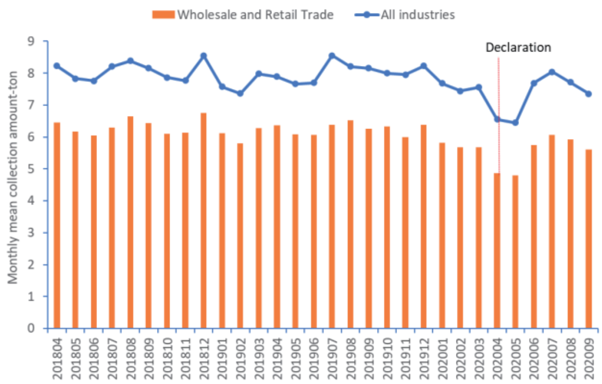

Figure 1. Monthly variations in the monthly-mean amount of industrial plastic waste (IPW) collected (tonnes) for all industries and for the wholesale and retail trade sector

As shown in Figure 1, the monthly-mean amount of IPW collected varied remarkably during the two and a half years of the study. Peak collection usually occurred in July, August, and December. The amount of IPW collected in February was lower than in other months. Because the Japanese government's first declaration of a state of emergency for Fukuoka was issued on April 7, 2020, the months with substantially dropped amounts were April and May 2020. The total amount of IPW collected from all industries since April 2018 to September 2020 was approximately 7,147 tonnes, 78% of which was from the wholesale and retail trade sector (5,539 tonnes). Due to its high proportion and trade-off specific (the decreased times for shopping while the increased commodity bought each time by customers affect the industrial plastic used for packing), the wholesale and retail trade sector was selected as our target. We found that trends in the amount of IPW collected from the wholesale and retail trade sector were similar to trends in the total amount collected from all industries. The substantially dropped collection amounts may be caused by the restrictions on the use of department stores in response to COVID-19. The monthly sales of department stores in Fukuoka were reduced by 82.1% in April and 64.8% in May 2020 compared to the same months in 2019[15]. As a major recycling company, it owns lots of collection target facilities mainly located in Fukuoka and Kitakyushu cities (Figure 2) where the shares of gross production of the wholesale and retail trade sector (76%) and all sectors (58%) are great in 2020 of Fukuoka Prefecture[16]. Once the IPW collection amount is demonstrated to correlate with the gross production, its monthly data are representative to track the trends in IPW collection in sectors of Fukuoka, at least to some extent.

Figure 2 shows the geographic distribution of the collection target facilities (173) and the total IPW collected during the study period. We found the areas with the highest collection records were in or near Fukuoka city. As shown in Figure 3, we explored correlations between the monthly amount of IPW collected and the monthly amount of wholesale and retail sales sector ($R^2 = 0.62$)[15]. The results imply that the amount of sales in the wholesale and retail trade sector can be used to predict the amount of IPW

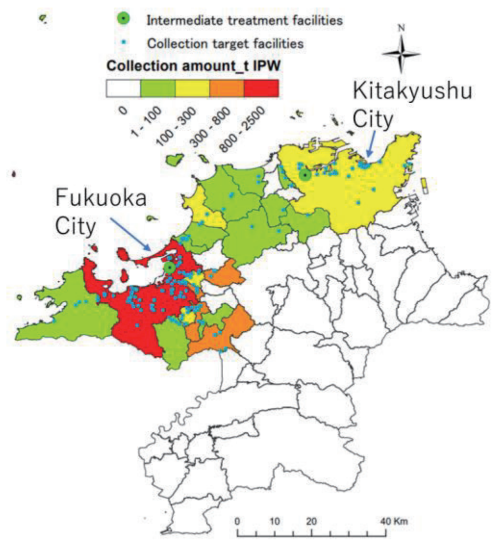

Figure 2. Geographic distribution of the collection target facilities and total amount collected (tonnes) per municipality

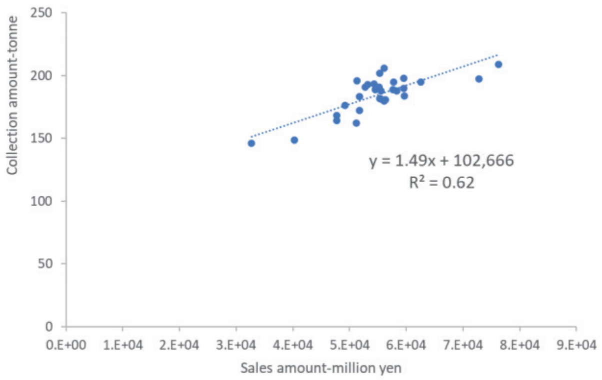

Figure 3. Correlation between amount of IPW collected monthly (tonnes) and monthly sales in the wholesale and retail trade sector (million yen)

generated by this sector.

2-2 COVID-19 Infection in Fukuoka Prefecture

We plotted the monthly rise in the cumulative number of patients with COVID-19 from February 2020 to June 2021 based on government-reported data[17]. As shown in Figure 4, there were several significant increases in the number of patients infected with COVID-19, especially in August 2020, January 2021, and May 2021.

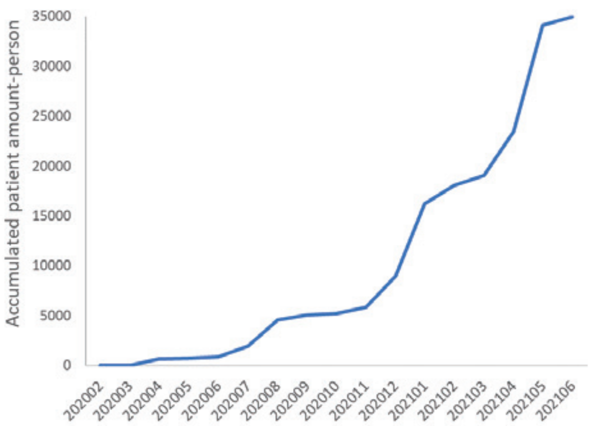

Figure 4. Monthly rise in the cumulative number of patients infected with COVID-19 in Fukuoka Prefecture

Figure 5 shows the geographic variation in cumulative counts of patients with COVID-19 at the end of May 2021. As indicated by the arrows, the top three cities with the highest numbers of such patients were Fukuoka (15,968), Kitakyushu (4,590), and Kurume (1,811).

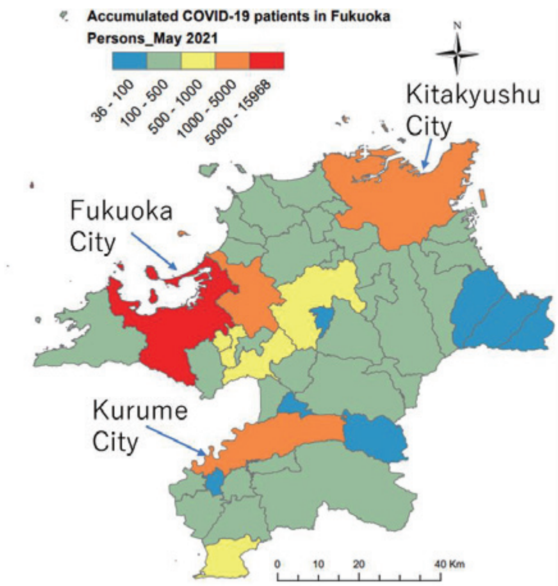

Figure 5. Geographic variation in the cumulative number of patients infected with COVID-19 at the end of May 2021

2-3 Prediction of Monthly IPW Collection Totals by Multiple Regression Analysis

In light of the previously demonstrated correlations, we conducted a multiple regression analysis using the monthly IPW collection total as the objective function, comparing it with the amount of sales in the wholesale and retail trade sector and with the monthly increase in the number of patients with COVID-19. The data from February to September in 2020 and the tool of regression analysis in excel was used. Our calculations confirmed that the monthly amount of IPW collected from the wholesale and retail trade sector was significantly correlated with the other two indicators ($R^2 = 0.94$).

2-4 Prediction of Daily IPW Collection Amount by Machine Learning

Because real socio-economic data, such as sales in the wholesale and retail trade sector, were not available at a daily level and were obviously not available for future months, the statistical approach had limited utility for predicting future daily IPW generation by individual

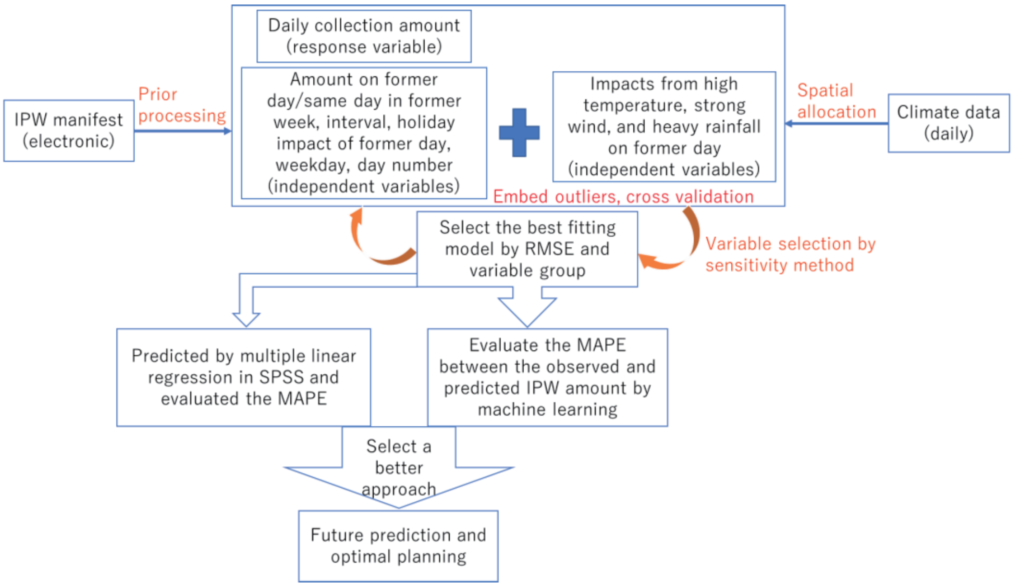

Figure 6. Workflow used to predict the industrial plastic waste (IPW) collection amount from the collection facilities in Fukuoka by machine learning

facilities. Thus, efforts were made to apply a machine learning (ML) approach to future prediction. These are described in the following paragraphs.

Figure 6 shows the workflow applied in developing an ML approach to future prediction for predicting the daily amount of IPW to be collected from individual facilities. Details on data processing will be described in the following paragraphs. We first performed prior processing for the waste manifest data and extracted the data for facilities from our target sector, the wholesale and retail trade sector. Next, we combined these data with daily weather data. We fit the data to multiple models and chose the best one by comparing their root mean square error (RMSE)[18]. The optimal variable group for the purpose of prediction was selected based on sensitivity[19]. After that, we conducted future prediction both by ML and by linear regression using Statistical Package for the Social Sciences (SPSS Statistics v.21). Finally, we evaluated the accuracy of both methods by mean absolute percentage error (MAPE)[20]. The RMSE and MAPE were calculated according to Equations 1 and 2, respectively,

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(f_i - y_i)^2} \tag{1}$$

$$\mathrm{MAPE} = \frac{100}{n}\sum_{i=1}^{n}\left|\frac{f_i - y_i}{y_i}\right|, \tag{2}$$

where

n: the number of data

y_i: the observed value of data i

f_i: the predicted value of data i

The raw manifest data contained individual records on daily amount collected (kg), collection date (from April 1, 2018, to September 30, 2020), facility name, intermediate treatment facilities (destinations of collections), and name of the collector for each collection. Industrial categories were recorded for all facilities to permit extraction of individual data for those belonging to the wholesale and retail trade sector. To ensure prediction accuracy, we added seven other independent variables besides the response variable (daily amount collected), as listed in Table 1. Two of these variables, what day it was the day and whether the previous day was a holiday, were determined by reference to the calendar. Because high temperatures, strong winds, and heavy rainfall can limit consumer activities and IPW collection, information on the previous day's weather was added to the model, based on the daily weather report[21].

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
Previous d_climate	category type on climate impact of previous day: wind speed >= 6 m s^{-1}, daily rainfall >= 5 mm, highest temperature >= 35 degree
Previous 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

Before fitting the model, we cleaned up the outliers in the data and divided our dataset into training data (80%) and test data (20%). Then, we performed cross-validation through repeated model fitting and selected the best model with the lowest RMSE. As shown in Table 2, the optimal ensemble model was chosen as our best model (RMSE = 0.9437). We found that the RMSEs for some models were significantly larger than those of others (linear SVM, quadratic SVM, cubic SVM, and all neural network models); this implies that these models were not suitable for fitting the training data.

Because there were a large number of variables that might affect the running time and accuracy of the prediction, we determined the optimal variable group according to sensitivity. For that purpose, all variables were standardized. Variable selection was performed as follows. First, predictions were made using all variables in the optimal ensemble model, and the RMSE between the predicted and observed values was calculated. Second, the independent variable of interest was given an observed value (x), while the others were given mean values, and the model was used to predict the response variables (y); this was repeated for each variable with the same model. Third, the R^2 of a line was estimated using two pairs of (x, y) for each independent variable. Fourth, the absolutized R^2 was calculated for each variable and used as an indicator of sensitivity. Fifth, the variable with the lowest sensitivity was deleted, and the first

Table 2. The root mean square error (RMSE) for all models explored by machine learning

Category	Model	RMSE
Linear regression	Linear regression	0.9935
	Interactions linear	0.9968
	Robust linear	1.0035
	Stepwise linear	0.9935
Decision tree	Fine tree	1.0743
	Medium tree	0.9901
	Coarse tree	0.9599
SVM	Linear SVM	38.2910
	Quadratic SVM	1.05E+18
	Cubic SVM	1.51E+35
	Fine Gaussian SVM	0.9917
	Medium Gaussian SVM	0.9828
	Coarse Gaussian SVM	0.9926
Ensemble	Boosted Trees	0.9463
	Bagged Trees	0.9472
Gaussian process regression (GPR)	Rational Quadratic	0.9810
	Squared Exponential	0.9818
	Matern 5/2	0.9798
	Exponential	0.9795
Neural Network	Narrow Neural Network	6.00E+15
	Medium Neural Network	1.91E+16
	Wide Neural Network	2.13E+16
	Bilayered Neural Network	4.85E+15
	Trilayered Neural Network	5.82E+15
Optimal models	Optimal tree	0.9539
	Optimal SVM	1.0006
	Optimal GPR	0.9567
	Optimal ensemble	0.9437

to fourth steps were repeated in a loop. Sixth, the selection process was continued until the minimum RMSE was obtained.

Table 3. The root mean square error (RMSE) and R^2 during the variable selection tests

Variable	R^2		
	Step1	Step2	Step3
Day_num	0.2537	0.1940	0.2642
Weekday	0.0016	0.0096	0.0168
Previous d_climate	0.0006	0.0021	Null
Previous d_holiday	0.0404	0.0527	0.0446
Interval	0	Null	Null
Num_fday	-0.0563	-0.0592	-0.0239
Num_sday_fw	-0.0755	-0.0305	-0.0375
RMSE (optimal ensemble)	0.9437	0.9416	0.9373

During the process, we found the RMSE started to increase (0.9504) when the variable Weekday was deleted, with the minimum sensitivity being reached at step 3 (Table 3). Thus, the variable selection process was ended at step 3 (RMSE = 0.9373), on which five variables were left in our optimal variable group.

3. Results and discussion

3-1 Predicted monthly IPW collection amount by statistical approach

Using the estimated multi-regression coefficients and the real statistical data on monthly sales in the wholesale and retail trade sector and increase in the number of patients with COVID-19, we predicted the monthly amount of IPW to be collected in Fukuoka Prefecture up to March 2021, as shown in Figure 7. The total amount of IPW collected from the wholesale and retail trade sector seemed to increase monthly until peaking in December 2020, then began declining at the beginning of 2021. This approach is easy to be used for predicting monthly collection amount of IPW, however, it is limited by the availability of the statistical data.

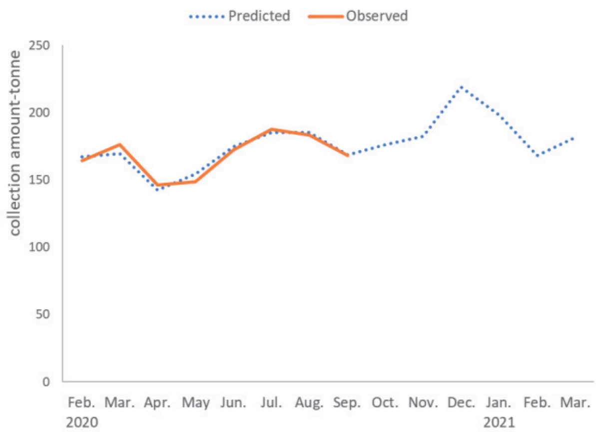

Figure 7. Future predictions regarding industrial plastic waste collection totals (tonnes) made by multiple linear regression

3-2 Predicted daily IPW collection amount by ML approach

Using the variable group and model determined to be optimal, we predicted the daily amount of IPW to be collected from one facility in the wholesale and retail trade sector over 7 days (September 1 to 8, 2020; no collection was recorded on September 7), then compared our predictions with the observed values. The MAPE for this period was calculated as 6.4%. Thus, the accuracy of our

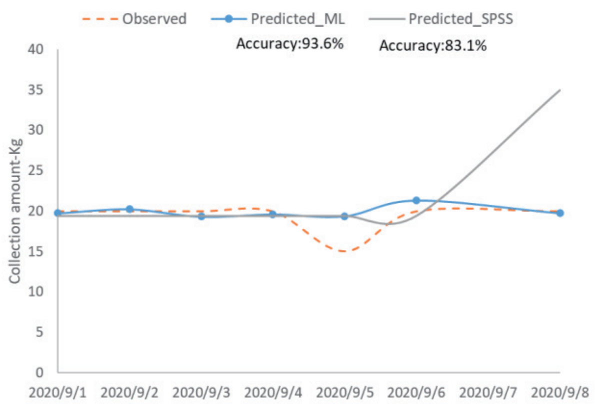

Figure 8. Validation of predicted (machine learning [ML] and SPSS) and observed values for amount of industrial plastic waste collected (kg) from September 1 to 8, 2020

prediction reached approximately 93.6% (Figure 8). Notably, the MAPE reached 9.3% when predictions were made with the same data without cleaning up the outliers; this implies that cleaning up outliers improves the accuracy of prediction. On the contrary, when we used the linear regression tool of SPSS to make predictions using the same data, the accuracy of the predictions was 83.1%. We concluded that in this case, the ML approach provided higher prediction accuracy than that of the statistical approach. The process we used to optimize our data and model could be used to improve the accuracy of future predictions.

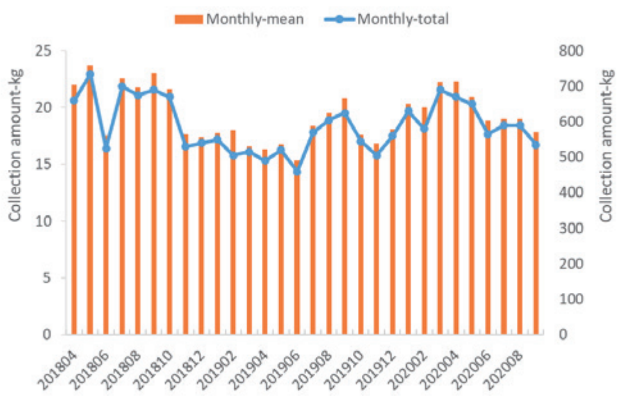

Figure 9. Monthly variations in the monthly-mean and monthly-total amounts (refer to right y-axis) of industrial plastic waste (IPW) collected from a supermarket in this period, unit: kg

Figure 9 shows the monthly variations in the monthly-mean and monthly-total amounts of IPW collected from a supermarket (ML target) during this period. We found that the monthly-mean IPW collection did not change so much even under the COVID-19 pandemic. It implies that the ML approach is reasonable to be used for the whole period.

As a further application, we used both ML and SPSS approaches to predict the amount of IPW generation from October 1 to 31, 2020. As shown in Figure 10, the maximum value predicted by ML was slightly larger than that predicted by SPSS, whereas the trend of values predicted by SPSS seemed to be smoother than that of

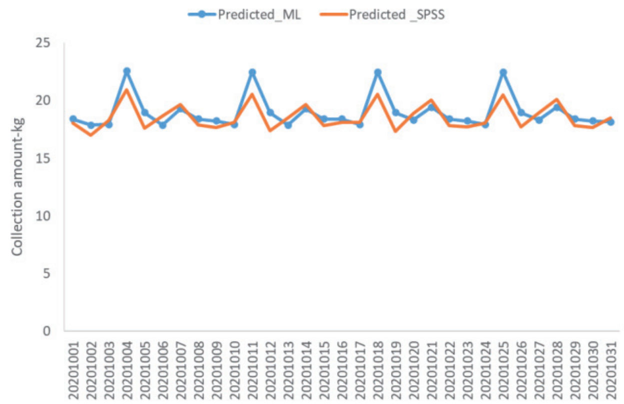

Figure 10. Future prediction using machine learning (ML) and SPSS approaches of daily amount of industrial plastic waste (kg) to be collected from a facility

values predicted by ML. As demonstrated above, the ML result is more suitable to be used for future applications. With the predicted collection demands from individual facilities, it is possible to support the recycling companies to make flexible collection schedules, integrate the current IPW collection system (spot-collection coexisted with the routing-collection) by a cyclic collection method, and optimize the collection route by special purposes e.g., cost, collection time, and vehicle assignment.

3-3 Limitations and future plans

There are some limitations to this approach. For example, more socioeconomic factors should be included in the multiple regression analysis, however, we only considered two independent variables due to data limitations. Moreover, we have not included the indexes of business conditions in our model e.g., consumer confidence index and Tokyo Stock Price Index which could be varied in the long term so as to affect daily IPW collection amount. Due to the limitation of future predictions on climate, the accuracy could be ensured for the coming week. Therefore, it forces our prediction on IPW collection amount in the coming week is reasonable to be used for solving social problems. As the accuracy of climate prediction is to be improved in the future, our results could be reasonably applied for a longer period. Even the ML approach could be applied for other facilities, data processing and future predictions need to be done case by case.

In the next step, we will further explore the optimal predictive variables by adjusting the background conditions of the variables so as to improve prediction accuracy. ML studies for other sectors will also be considered. More focus will be placed on devising applications of this work, such as solving optimal routing problems, optimizing systems, and evaluating both the optimal case and the current state of affairs.

4. Conclusions

In this study, we assessed the status of IPW collection in Fukuoka Prefecture based on manifest data from a local recycling company. The monthly mean and monthly total collection amount of IPW from all industries were greatly impacted by the COVID-19 pandemic, especially in April and May 2020 corresponding to the first declaration of a state of emergency. Beyond our expectation, there was a special case from a supermarket where the daily IPW collection amount did not affect by this pandemic. Through the analysis, we found a good correlation between IPW amounts collected and two other socio-economic factors, one being the amount of wholesale and retail sales sector, the other being the number of people infected with COVID-19. Furthermore, we developed a detailed method of future prediction using an ML approach and validated its accuracy by comparison with prediction using a statistical tool in SPSS. The comparison showed that in this case, the ML approach produced more accurate predictions than SPSS. However, the statistical approach is easier to perform and can be used even if the data volume is small. Although the ML approach can achieve higher accuracy, it requires “big data” and more work to process the data.

This study demonstrated that waste manifest data are useful not only for illuminating trends in IPW collection but also for making future predictions regarding IPW collection. This approach can help local recycling companies optimize their collection and disposal schedules, vehicle routing and deployment choices, and personnel arrangements.

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