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Short Communication

Modeling of municipal waste disposal rates during COVID-19 using separated waste fraction models

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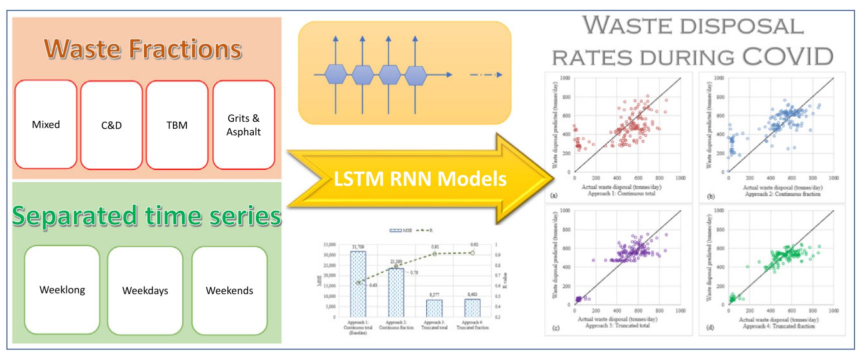
HIGHLIGHTS

- Variabilities of municipal solid waste disposal data during COVID were quantified.
- Four modeling approaches were attempted to predict waste disposal during lockdown.
- The use of waste fractions in modeling improves both model accuracy and precision.
- The use of separated time series better captures COVID waste disposal behaviors.

GRAPHICAL ABSTRACT



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ABSTRACT

Municipal waste disposal behaviors in Regina, the capital city of Saskatchewan, Canada have significantly changed during the COVID-19 pandemic. About 7.5 year of waste disposal data at the Regina landfill was collected, verified, and consolidated. Four modeling approaches were examined to predict total waste disposal at the Regina landfill during the COVID-19 period, including (i) continuous total (Baseline), (ii) continuous fraction, (iii) truncated total, and (iv) truncated fraction. A single feature input recurrent neural network model was adopted for each approach. It is hypothesized that waste quantity modeling using different waste fractions and separate time series can better capture disposal behaviors of residents during the lockdown. Compared to the baseline approach, the use of waste fractions in modeling improves both result accuracy and precision. In general, the use of continuous time series over-predicted total waste disposal, especially when actual disposal rates were less than 50 t/day. Compared to the baseline approach, mean absolute error (MAE), mean absolute percentage error (MAPE), and mean square error (MSE) were reduced. The R value increased from 0.63 to 0.79. Comparing to the baseline, the truncated total and the truncated fraction approaches better captured the total waste disposal behaviors during the COVID-19 period, probably due to the periodicity of the weeklong data set. For both approaches, MAE and MAPE were lower than 70 and 22%, respectively. The model performance of the truncated fraction appears the best, with an MAPE of 19.8% and R value of 0.92. Results suggest the uses of waste fractions and separated time series are beneficial, especially if the input set is heavily skewed.

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1. Introduction

1.1. Modeling of waste generation and disposal rates

Waste quantity modeling plays an important role in day-to-day waste management planning and operation (Vu et al., 2019a; Smejkalova et al., 2020), as well as the overall design and implementation of any circular economy (Magazzino et al., 2021; Zhang et al., 2021). Municipal solid waste (MSW) generation, recycling, and disposal behaviors are complex and related to various socioeconomic (Bruce et al., 2016; Chowdhury et al., 2017), geographical, and demographic factors (Younes et al., 2015; Coskuner et al., 2020). Due to its practical importance and environmental significance, studies on waste quantity modeling and forecasting have been widely studied and reported across the globe. Traditionally, quantitative waste forecasts and identification of causal factors were conducted using time series and regression analysis techniques. Rimaitytė et al. (2012) used various regression models to forecast weekly waste generation in Kaunas, Lithuania and found that waste forecasts were sensitive to various social-economic indicators. Denafas et al. (2014) applied time series analyses and successfully estimated monthly generation of MSW and 11 waste fractions in 4 cities in East European countries using selected social-economic factors. Ghinea et al. (2016) adapted prognostic tools, regression analysis, and time series analysis to obtain regression equations for 6 waste fractions in Romania, and found that the S-Curve trend model accurately predicts MSW generation with a mean percentage error of 2%. Regression techniques were performed by Grazhdani (2016) to predict annual waste generation in Prespa Park, Albania. Grazhdani (2016) reported a significant correlation between higher education level and lower per-capita waste generation, among various social-economic factors.

Recently, there has been an increase in the use of machine-based approaches for waste quantity modeling globally (Xu et al., 2021). For example, artificial neural network (ANN) time series with multi-variate features were successfully applied to model weekly solid waste generation in the Middle East (Noori et al., 2010; Shahabi et al., 2012), North America (Kontokosta et al., 2018), and Europe (Cubillos, 2020). ANN and other neural network models are useful for mapping complex non-linear problems, and are particularly suitable for waste quantity estimation with a larger dataset. For example, Azadi and Karimi-Jashni (2016) applied a multi-variate features ANN to predict seasonal waste generation rates in 20 Iranian cities and reported a mean percentage error ranging from 6% to 17%. Kannangara et al. (2018) used regression trees and neural networks to predict residential waste generation in 220 cities in Ontario, Canada, with mean percentage errors varying from 19% to 34% in the testing stage. Wu et al. (2020) conducted a large-scale ANN waste modeling study using regional data in China and reported promising model performance, with root mean square error over 0.94 in all regions.

Some waste studies compared ANN approaches with regression techniques directly and reported superior model accuracy using ANN approaches. Jahandideh et al. (2009) modeled hospital waste in Iran using both ANN and multiple linear regression, and found that ANN models were generally more accurate with an R^2 of 0.99 for all four types of hospital waste. Azadi and Karimi-Jashni (2016) compared ANN and regression model performance on MSW generation using 5 different performance indicators and concluded that ANN was consistently better. Similar results were reported by Sun and Chungpaibulpatana (2017) in a MSW forecast study in Bangkok, Thailand. Oliveira et al. (2019) compared ANN and regression analysis on household packaging waste modeling, and concluded ANN model performance using R^2 was 34% higher than non-linear regression models.

COVID-19 and the subsequent lockdowns have significantly impacted MSW disposal behaviors (Kulkarni and Anantharama, 2020; Fan et al., 2021; Richter et al., 2021b). Similar observations were reported on food waste (Burlea-Schiopoiu et al., 2021), plastic wastes (Vanapalli et al., 2021), household wastes (Ikiz et al., 2021), and health care wastes (Manupati et al., 2021). Simple regression models often failed to address the non-linearity of the data, and it is hypothesized that an advanced numerical model is required to fully capture the waste disposal behaviors during the pandemic. Since COVID-related regulations have impacted different waste streams differently (Richter et al., 2021a; Richter et al., 2021b), an ANN-based study on modeling of different waste fractions during the pandemic is of practical interest.

1.2. Modeling with different waste fractions and time scales

Some researchers have applied different ANN-based waste quantity models on different waste fractions to improve modeling accuracy. Batinic et al. (2011) adopted multi-variate features of multilayer perceptron ANN to predict 6 waste fractions including organic waste, paper, plastics, glass, metals, and other waste in Serbia, and obtained acceptable mean absolute percentage error. Coskuner et al. (2020) used multi-variate features multilayer perceptron ANN to predict domestic, commercial, and construction waste generation in Askar Landfill, the Kingdom of Bahrain. Using different social, demographic, economic, geographical, and touristic factors, Coskuner et al. (2020) reported satisfactory model accuracy, especially with respect to commercial waste modeling.

ANN-based modeling has also been applied on different time scales. Younes et al. (2015) identified the key factors to predict annual waste generation in Malaysia using an adaptive neuro-fuzzy inference system. Abbasi and El Hanandeh (2016) explored various intelligent system algorithms, including ANN, to forecast monthly waste generation in Logan city, Australia. They concluded that all models have good prediction performance and could be applied to conduct accurate municipal waste forecasts. Ali and Ahmad (2019) applied an ANN time series model with autoregressive technique to forecast the monthly solid waste generation in Kolkata, India, and reported satisfactory results in both training and testing stages. Moreover, ANN modeling on waste quantity was attempted with weekly (Vu et al., 2019a) and daily data (Nabavi-Pelesaraei et al., 2017). The literature review suggests an ANN modeling approach is applicable to long-, medium-, and short-term waste forecast.

1.3. Novelty, objectives, and practical implications

The ANN waste modeling studies discussed focus on either total waste estimation or waste fractions prediction. However, there is no study that explicitly considers the difference between the waste modeling approaches (total waste vs. total waste from fractions). Recent studies suggested that waste disposal behaviors of different waste streams evolved differently during COVID-19 (Richter et al., 2021a; Richter et al., 2021b), as such modeling individual waste fractions separately and combining them for the total waste quantity is more advantageous from a theoretical standpoint. It is hypothesized that waste quantity modeling using different waste fractions and separate time series can better capture disposal behaviors of residents during the lockdown. The use of distinct time series on model accuracy is seldom reported in the literature. Unlike other studies, this waste quantity study focuses on the differences in modeling performance using the four modeling approaches.

In this study, total waste disposal was computed and compared using single feature long short-term memory (LSTM) recurrent neural network (RNN) models with four different approaches including continuous total, continuous fraction, truncated total, and truncated fraction. The objectives of this short communication were to (i) examine the potential benefits of waste fractions-based modeling on MSW disposal rates during the COVID-19 period and (ii) examine the effect of distinct time series on model accuracy. The results are important and have significant practical implications on the planning and operation of waste disposal sites during and after the pandemic, or other emergencies.

1.4. Study area

Regina, the capital city of Saskatchewan, Canada was selected as the study area. The waste disposal characteristics and distributions were reported in a previous study (Richter et al., 2021). According to the latest census data from Statistics Canada (2016), the population in Regina was 236,500 in 2016. The average daily total waste disposed of at the Regina landfill from 2013 to 2020 was about 555.08 t/day, including 349.35 t/day of mixed waste, 194.93 t/day of construction and demolition (C&D) waste, 8.64 t/day of treated bio-medical (TBM) waste, and 14.02 t/day of grit and asphalt (City of Regina, 2020). The northern part of the Regina landfill does not have an engineered liner (Pan et al., 2019a, 2019b), but has a landfill gas management system (Bruce et al., 2017; Bruce et al., 2018).

A provincial state of emergency was first declared on March 18th, 2020. In this study, COVID-19 period is defined from March 18th, 2020 to September 12th, 2020. Over 1709 COVID-19 positive cases with 24 deaths were reported in Saskatchewan on September 12, 2020 (Government of Saskatchewan, 2020). The Regina landfill is the sole municipal landfill in the area and receives wastes from nearby regions. The landfill is open 7 days per week in summer and 6 days per week in winter (City of Regina, 2020), partly because of a higher amount of yard and C&D wastes during summer months. Major maintenance and construction projects for roads, drainage networks, and wastewater facilities also occur during the summer months (City of Regina, 2021).

2. Methodology

2.1. Data collection and processing

About 7.5 years of daily waste disposal records of (i) mixed waste, (ii) C&D waste, (iii) TBM waste, and (iv) grit and asphalt from January 1st, 2013 to September 12th, 2020 was collected from City of Regina. The total waste is the sum of all waste types. Three separate time series including week-long, weekday, and weekend sets were developed for the total waste and the 4 waste fractions. The weekday set covers truncated time series from Monday to Friday, and the weekend set compiles truncated time series from Saturday to Sunday. The week-long set is from Monday to Sunday. The methodological flowchart is shown in Fig. 1. To test the robustness of the four modeling approaches, no data points were removed and all data were considered in the modeling.

2.2. Effects of waste fractions on total waste disposal predicted

Five single feature RNN-LSTM models were developed using Tensorflow 2.0, using modified open-source code from Valkov (2019). The ratio of training stage and testing stage was selected at 80:20 (Azadi and Karimi-Jashni, 2016; Kannangara et al., 2018; Wu et al., 2020).

2.2.1. Approach 1 - continuous total waste disposal prediction

Approach 1 (continuous total) is a single feature RNN-LSTM model for the estimation of total waste disposal during the COVID period (Model 1a, Fig. 1). This also serves as the benchmark of the study. Week-long total waste disposal data from the entire 7.5-year study period was used as the input of Model 1a. The model consists of 2 hidden layers with 600 neurons in each layer, and a lag time of 10 days. The number of hidden layers, neurons, and lag time were determined from the preliminary trials.

2.2.2. Approach 2 - continuous fraction prediction

In Approach 2 (continuous fraction), four RNN-LSTM models were built including mixed waste (Model 1b), C&D waste (Model 1c), TBM waste (Model 1d), and grit and asphalt (Model 1e) (Fig. 1). The input for each model was the week-long continuous time series of each respective waste stream. The results of the four models (Outputs 1b, c, d, e) were then combined to estimate the total waste disposal. The results were compared to the baseline case (Output 1a). The structure of the four models, the ratio of training to testing stages, lag times were identical to the baseline (Model 1a).

2.3. Effects of distinct time series on total waste disposal predicted

Two approaches with 10 single feature RNN-LSTM models were developed to examine the effects of waste disposal fractions on the total waste disposal predicted during the COVID-19 period, as discussed in Sections 2.3.1 and 2.3.2.

2.3.1. Approach 3 - truncated total waste disposal prediction

In Approach 3 (truncated total), 2 single feature RNN-LSTM models (models 2.1a and 2.2a, Fig. 1) were developed to predict total waste disposal during the COVID period. In this approach, "total waste disposal weekday truncated time series" data from January 1st, 2013 to September 12th, 2020 was used as the input of Model 2.1a (weekday total model) while the total waste disposal weekend truncated time series data was used as the input of Model 2.2a (weekend total model). The two models consisted of 2 hidden layers, with the number of neurons of each hidden layer of 600, lag time of 10 days for the weekday total model, and lag time of 2 weeks for the weekend total model, as determined by the preliminary trials. The result of the weekday total model (Output 2.1a) for the COVID-19 period was combined with the result of the weekend total model (Output 2.2a) to compute the final outputs.

2.3.2. Approach 4 - truncated fraction prediction

In Approach 4 (truncated fraction), eight RNN-LSTM models (Fig. 1) were built, as discussed below.

- A weekday mixed waste model (Model 2.1b) with the input of weekday truncated time series of mixed waste, and a weekend mixed waste model (Model 2.2b) with the input of weekend truncated time series data of mixed waste.
- A weekday C&D waste model (Model 2.1c) with the input of weekday truncated time series of C&D waste, and a weekend mixed waste model (Model 2.2c) with the input of weekend truncated time series data of C&D waste.
- A weekday TBM waste model (Model 2.1d) with the input of weekday truncated time series of TBM waste, and a weekend TBM waste model (Model 2.2d) with the input of weekend truncated time series data of TBM waste.
- A weekday grit and asphalt waste model (Model 2.1e) with the input of weekday truncated time series of grit and asphalt waste, and a weekend grit and asphalt waste model (Model 2.2e) with the input of weekend truncated time series data of grit and asphalt waste.

Each of the eight models consisted of 2 hidden layers, with the number of neurons of each hidden layer of 600, lag time of 10 days for the weekday mixed waste, C&D waste, TBM waste, grit and asphalt waste models and lag time of 2 weeks for those of weekend models. The results of the sub-models (Outputs 2.1b, 2.2b, 2.1c, 2.2c, 2.1d, 2.2d, 2.1e, and 2.2e) were combined to compare with the baseline (Output 1a) and other approaches.

2.4. Models' performance assessment

Common metrics to assess ANN model performance include mean absolute error (MAE), mean absolute percentage error (MAPE), mean square error (MSE), and correlation coefficient (R). Unlike the error terms (MAE, MAPE, and MSE), the R value ranges from −1 to +1. The closer R value to +1, the more accurate the results. These four metrics were also adopted by others (Vu et al., 2019a, 2019b; Fallah et al., 2020; Coskuner et al., 2020). The following equations were used to calculate the model assessment metrics.

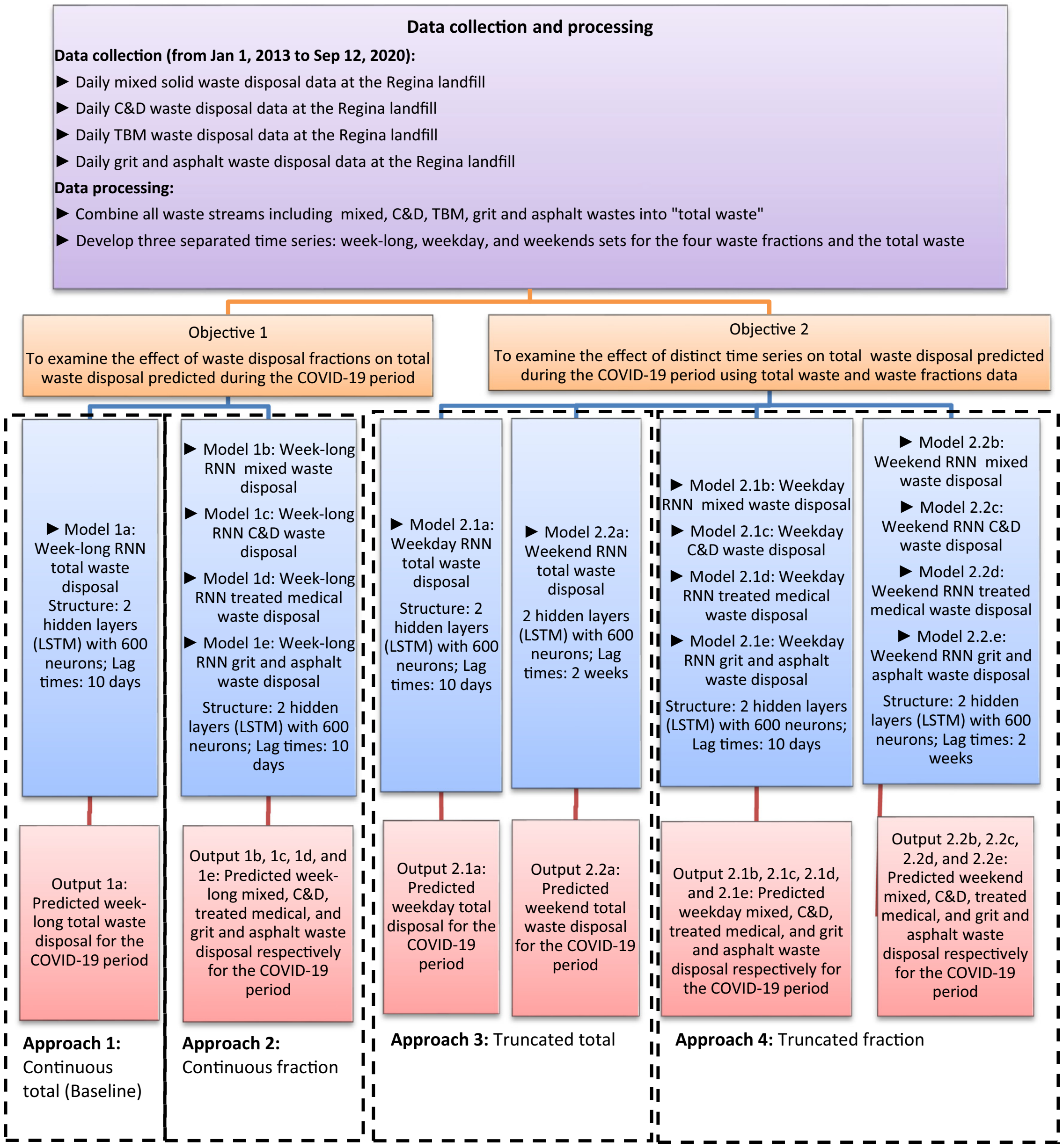

Fig. 1. Methodology flow chart.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|Y_a^i - Y_p^i| \quad (1)$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{Y_a^i - Y_p^i}{Y_a^i}\right| \times 100 \quad (2)$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(Y_a^i - Y_p^i\right)^2 \quad (3)$$

$$R = \frac{\sum_{i=1}^{n}\left(Y_p^i - \overline{Y_p}\right) \times \left(Y_a^i - \overline{Y_a}\right)}{\sum_{i=1}^{n}\left(Y_p^i - \overline{Y_p}\right) \times \sum_{i=1}^{n}\left(Y_a^i - \overline{Y_a}\right)} \quad (4)$$

where:

n: Number of data points
Y_a: Actual mass of total waste disposal
Y_p: Predicted mass of total waste disposal
$\overline{Y_a}$: The mean actual mass of total waste disposal
$\overline{Y_p}$: The mean predicted mass of total waste disposal.

3. Results and discussion

3.1. Data characteristics and analysis

3.1.1. Week-long data set

Data skewness and distribution are first examined as they may impact the performance of the predictive models. Table 1 shows the range and variability of the daily disposal data at the Regina landfill. The counts of the week-long set ranged 1324 (TBM waste) to 2602 (total waste), indicating TBM disposal is uncommon. Unlike other waste streams, TBM was delivered to the landfill about 3 times per week during the study period. For the week-long set, it is observed that mixed and C&D wastes accounted for the largest portions of waste disposed of at the landfill, representing 62.9% and 35.1%, respectively. TBM waste, on the other hand, represents only about 1.6% of total waste disposed. TBM waste disposal was less frequent and the

Table 1
Waste disposal data in Regina landfill in the period of Jan 1st, 2013 to Sep 12th, 2020.

	Count	Min	Mean	Max	Min/max	STDEV	STDEV/mean
Unit	N/A		(t/day)		N/A	(t/day)	N/A
Week-long data							
Total waste	2602	0.18	555.08	1444.13	0.00012	309.56	0.56
Mixed waste	2576	0.04	349.35	886.96	0.00005	207.78	0.59
C&D waste	2579	0.18	194.93	822.65	0.00022	152.43	0.78
TBM waste	1324	0.05	8.64	25.34	0.00197	4.14	0.48
Grit and asphalt	2156	0.04	14.02	115.00	0.00035	14.08	1.00
Weekday data							
Total waste	2003	77.01	694.97	1444.13	0.05333	196.08	0.28
Mixed waste	2003	77.01	440.46	886.96	0.08682	134.02	0.30
C&D waste	1990	0.73	237.85	822.65	0.00089	146.70	0.62
TBM waste	1023	0.05	8.90	25.34	0.00197	4.36	0.49
Grit and asphalt	1739	0.04	15.73	115.00	0.00035	14.85	0.94
Weekend data							
Total waste	399	22.31	131.36	461.97	0.04829	76.22	0.58
Mixed waste	398	0.04	44.68	209.33	0.00019	32.01	0.72
C&D waste	392	0.72	74.99	338.61	0.00213	59.98	0.80
TBM waste	300	2.24	7.80	14.81	0.15125	3.09	0.40
Grit and asphalt	272	0.13	10.63	58.99	0.00220	10.61	1.00

average daily disposal rate was also the lowest (8.64 t/day). Mixed waste disposal had the smallest min-to-max ratio value of 0.00005, representing of the largest difference in the daily extreme values. Generally, more data variation is observed in grit and asphalt waste with a coefficient of variation (CV = stdev / mean) of 1.00. The CV for total waste (0.56) is less than the mixed and C&D wastes because of the larger set.

The minimum total waste disposal was observed on Sunday Jun 11th, 2017 (0.18 t/day), and the maximum total waste disposal was observed on Thursday May 15th, 2014 (1444.13 t/day), concurrently on the date with the highest C&D disposal. The maximum disposal rate for mixed and C&D waste were both observed on Thursdays (May 16th, 2013 and May 15th, 2014, respectively). On the other hand, minimum disposal rates were generally observed on the weekend due to no publicly funded collection service.

3.1.2. Weekday data set

The mean daily disposal rate of all waste streams disposed of during the weekday (Monday to Friday) was higher than that of the week-long data set (Table 1). This is due to the lower disposal rates during weekend, as further discussed in Section 3.1.3. The min-to-max ratio for TBM, grit and asphalt waste remained constant at 0.00197 and 0.00035, respectively. The min-to-max ratio for mixed waste, however, increased significantly from the lowest among the waste streams to the highest among the waste streams at 0.08682. Large differences in disposal behaviors were observed for the mixed waste between weekday and weeklong sets. With the exception of TBM waste, the CV of all waste streams reduced compared to that of the week-long data set. It appears the waste disposal behaviors at Regina landfill were much more consistent on weekdays.

3.1.3. Weekend data set

Mean disposal rates of total waste, mixed waste, C&D waste, TBM waste, and grit and asphalt for the weekend data set were 131.36, 44.68, 74.99, 7.8, and 10.63 t/day, respectively (Table 1). The mean disposal rates of all waste streams in the weekend set were noticeably

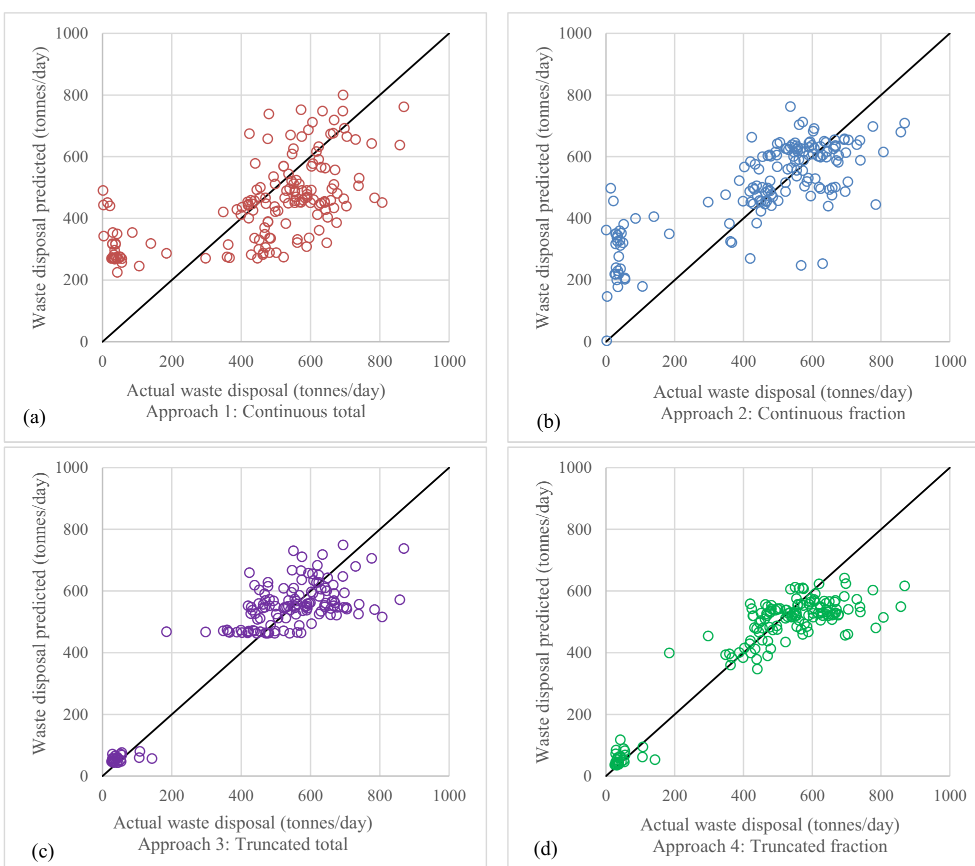

Fig. 2. Comparison between actual and predicted waste disposal at Regina landfill using a) Approach 1: Continuous total; b) continuous fraction; c) truncated total; d) truncated fraction.

smaller. For example, the mean mixed waste disposal rate was about 10 times lower than that of the weekday data set (440.46 t/day). This is probably due to the successful publicly funded curbside waste collection program operating on weekdays in Regina. A minimal min-to-max ratio (0.00019) was again observed for the mixed waste. With the exception of TBM, the CV of all waste streams increased from the weekday set, despite a much lower data count (272–399). The results suggested that truncated data sets may be able to improve predictive model performance due to the significant differences in the characteristics of the waste disposal sets.

3.2. Effects of waste fractions and distinct time series on total waste disposal modeling

Fig. 2 shows the comparison of four approaches for total waste disposal at the Regina landfill during COVID-19. The horizontal axis was the actual total waste disposal and the vertical axis was the total waste disposal predicted using the model. Fig. 2a demonstrates the comparison of total waste predicted during the COVID-19 period using Approach 1 (the baseline approach). Approach 1 generally underpredicted total waste disposed as there were some points under the 45-degree line (Fig. 2a). Approach 2 (Continuous fraction) had a better prediction in total waste disposal compared to the baseline, and the modeling results are relatively more accurate and precise especially in mid- data range. However, it has a tendency to over-estimate total waste disposal as slightly more points were over the 45-degree line (Fig. 2b). Comparison of Fig. 2a and b suggests (i) waste quantity modeling by fractions helped to improve both accuracy and precision in mid-range, and (ii) both continuous models failed to capture true disposal rates when actual rates were below 50 t/day. In lower disposal rates (i.e. during weekends), the ratio of overprediction (predicted/actual) can reached over 40 (Fig. 2a, b), undermining its usefulness as a predictive model.

Modeling waste disposal rates using separate time series requires more work, however it appears a better modeling approach, at least using waste disposal data in the current study. Comparing to the baseline, approaches 3 (truncated total) and 4 (truncated fraction) better captured the total waste disposal behaviors during the COVID-19 period (Fig. 2c, d), probably due to the periodicity of the weeklong data set. Both approaches 3 and 4 accurately predicted total waste disposal rates in the full range. Substantial improvements in model performance were observed below 50 t/day. Approach 4 appears slightly better, with more points located directly on the 45-degree line (Fig. 2d).

Fig. 3 presents model performance indicators for the four approaches. It is obvious that the use of waste fractions helps to reduce the modeling errors and increase R value. Compared to the baseline approach, the MAE of approach 2 decreased from 145.45 to 114.53, and the MAPE decreased from 625.92% to 391.54% (Fig. 3a). The MSE was reduced by 26.2% from 31,709 to 23,390 and R value increased from 0.63 to 0.79 (Fig. 3b). The results highlight the potential benefits of modeling total disposal rate using different waste fractions.

Model performance of approaches 3 (truncated total) and 4 (truncated fraction) were similar. Both were able to improve model accuracy of waste disposal behaviors during COVID-19 at Regina. For both approaches, the MAE and MAPE were lower than 70 and 22%, respectively. The model performance of Approach 4 appears slightly better than that of Approach 3 with an MAE of 66.7, MAPE of 19.8%, R value of 0.92. The MSE of approach 4 was, however, slightly higher at 8483. Since error was squared in MSE (Eq. (3)), the performance indicator was more sensitive to outliers. In general, the use of waste fractions and separate time series (approach 4) is recommended, especially if the continuous set is heavily skewed, such as the distinct disposal behaviors observed between weekdays and weekends in Regina landfill. The input sets (daily disposal records) are skewed in this study due to the publicly funded waste collection program. Similar waste collection programs are used in majority of industrialized nations. As such we believe the findings reported are applicable to other cities and countries.

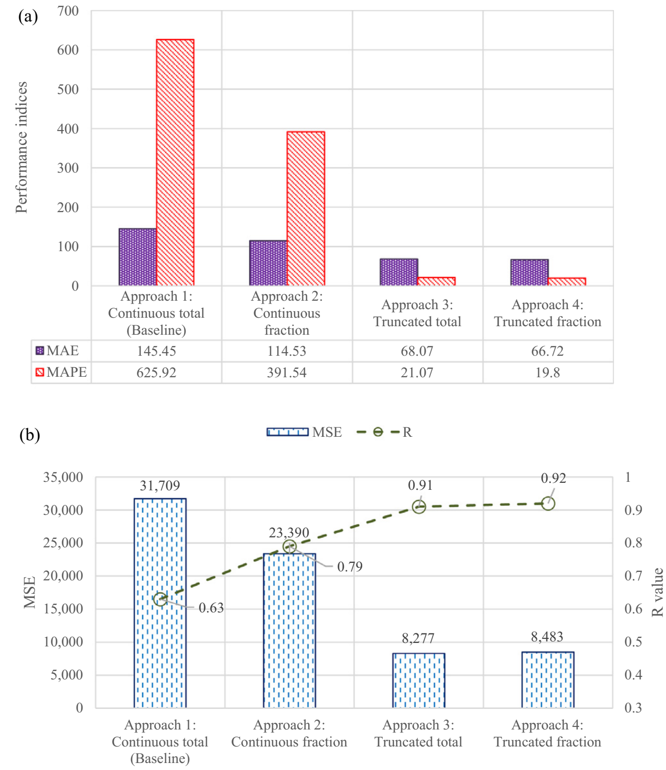

Fig. 3. Model performance comparison among Approach 1 - Continuous total (Baseline), Approach 2 - Continuous fraction, Approach 3 - Truncated total, and Approach 4 - Truncated fraction a) mean absolute error (MAE) and mean absolute percentage error (MAPE); b) mean square error (MSE) and R value.

4. Conclusion

A previous study indicated that waste disposal behaviors in Regina, the capital city of Saskatchewan, have changed significantly during the COVID-19 pandemic. In this short communication, variabilities of waste disposal data were first quantified using descriptive statistics. A total of four modeling approaches were explored to predict total waste disposal in Regina, including (i) continuous total (baseline), (ii) continuous fraction, (iii) truncated total, and (iv) truncated fraction. A single feature input RNN model was adopted for each approach. The result showed that the conventional approach (the baseline model) performed worst in modeling waste disposal behaviors during COVID-19. The use of waste fractions in modeling improves both model accuracy and precision compared to the baseline approach. In general, the use of continuous time series over-predicted total waste disposal in this study, especially when actual disposal rates were less than 50 t/day (i.e. during weekends). In some cases, the ratio of overprediction can reach over 40, undermining its usefulness. Compared to the baseline approach, MAE, MAPE, and MSE were reduced. The R value increased from 0.63 to 0.79. The results highlighted the potential benefits of modeling total disposal rates using different waste fractions.

Comparing to the baseline, the truncated total and the truncated fraction better captured the total waste disposal behaviors during the COVID-19 period, probably due to periodicity of the weeklong data sets. Substantial improvements of model performance using separate time series were observed for disposal rate below 50 t/day. For both approaches, MAE and MAPE were lower than 70 and 22%, respectively. The model performance of the truncated fraction appears the best, with MAPE of 19.8% and R value of 0.92. In general, the use of waste fractions and separated time series is recommended, especially if the input set is heavily skewed.

CRediT authorship contribution statement

Hoang Lan Vu: Writing – original draft, Conceptualization, Methodology. **Kelvin Tsun Wai Ng:** Conceptualization, Methodology, Supervision. **Amy Richter:** Formal analysis, Writing – review & editing. **Nima Karimi:** Writing – review & editing. **Golam Kabir:** Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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