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RESEARCH ARTICLE

Application of periodic parameters and their effects on the ANN landfill gas modeling

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Abstract

To reach a practical landfill gas management system and to diminish the negative environmental impacts from landfills, accurate methane (CH_4) prediction is essential. In this study, the preprocessing steps including minimizing multicollinearity, removal of outliers, and errors with missing data imputation are applied to enhance the data quality. This study is the first at employing periodic parameters in the two-stage non-linear auto-regressive model with exogenous inputs (NARX) with the aim of providing a convenient and precise approach to predict the daily CH_4 collection rate from a municipal landfill in Regina, SK, Canada. Using a stepwise procedure, various volumes of training data were assessed, and concluded that employing the 3-year training data reduced the mean absolute percentage error (MAPE) of the CH_4 prediction model by 26.97% at the testing stage. The favorable artificial neural network model performance was obtained using the day of the year (DOY) as a sole input of the time series model with MAPE of 2.12% showing its acceptable ability in CH_4 prediction. Using an only DOY-based model is especially remarkable because of its simplicity and high accuracy showing a convenient and effective approach in time landfill gas modeling, particularly for the landfills with no reliable climatic data.

Keywords Methane rate prediction · Artificial neural networks · MLP · NARX · Month of the year · Day of the year

Introduction

North America's solid waste generation and disposal rate is one of the highest in the world. Landfilling is a main solid waste management treatment in Saskatchewan, a Canadian province with a cold semi-arid climate with a disposal rate of about 86% higher than that of national (Statistics Canada 2010). Generation of greenhouse gas (GHG) and leachate are the major concerns with landfills. There are a number of studies on landfill gas (LFG) and leachate modeling due to the importance of GHG emission and groundwater pollution (Li et al. 2011; Abushammala et al. 2014; Mohsen et al. 2019; Fallah et al. 2019). In Canada, due to the high disposal rates, GHG emissions from the waste management systems increased by 15.2% from 1990 to 2006 and more than 90% of total Canadian GHG within the waste management sectors were generated from landfills (Environment Canada 2015).

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Landfill gas modeling

Methane (CH_4) (60%) and carbon dioxide (CO_2) (40%) are the major landfill gases generated from the anerobic decomposition of the degradable solid waste. CH_4 emission to the atmosphere with 25 times the potential damage imposed by CO_2 has been a major concern in global warming over the past hundred-year period (IPCC 2007). LFG collection systems, as the most common method in North America, are applied to reduce global warming potentials to the environments as well as to mitigate gas emissions from landfills by utilizing CH_4 for heating or electricity production through LFG flaring (Tolaymat et al. 2010; Rajaram et al. 2011; Sanchez 2016). Using flare systems, collected CH_4 is converted to CO_2 with less potential of global warming. Due to the contributions of GHG emissions and the explosive risk of methane gas, quantification of CH_4 collection rate from landfills is of high importance (Perera et al. 2002). Accurate CH_4 collection forecasts are needed for studying the feasibility of LFG management system design and operation and to warrant environmental assessment. An accurate prediction model helps the energy recovery to be done at the proper time, therefore helping to lower CH_4 environmental impacts (Ozkaya et al. 2007). In LFG management, numerical models have been developed for LFG predictions since direct measurements at the surface of the landfills are more costly. Numerical studies on LFG prediction are commonly reported in the literature (Ozkaya et al. 2007; Scozzari 2008; Thompson et al. 2009; Li et al. 2011; Amini et al. 2013; Mohsen et al. 2019) due to their practical importance.

ANN modeling in in predicting methane

Recently, artificial neural network (ANN) models have been widely used in air pollution modeling to predict GHG concentrations in various atmospheric science studies (Gardner and Dorling 1999; Li et al. 2011; Abushammala et al. 2014; Arhami et al. 2013; Radojević et al. 2018). The main advantage of the neural networks is their ability to learn and identify the complex relationship between inputs and outputs directly from training data (Kukkonen et al. 2003; Jiang et al. 2004). Owing to ANN models' generalization ability and computational efficiency, many GHG studies confirmed that ANN-based models provide more precise alternatives than the conventional statistical methods such as multilinear regression (Chelani et al. 2002; Sahin et al. 2005) especially, when the relationship of data is highly non-linear (Shi 2002; Karacan 2008).

Multilayer perceptron (MLP) neural network models have been adapted in various LFG studies. In predicting the CH_4 fraction of LFG in a bioreactor landfill in Turkey, Ozkaya et al. (2007) applied a back propagation MLP neural network model with one hidden layer. Scozzari (2008) applied an ANN model with meteorological input parameters to identify the biogas flux generated from the municipal solid waste landfill. In southern California, USA, Li et al. (2011) presented a back propagation MLP neural network model to predict methane, carbon dioxide, oxygen concentrations, and temperature in a landfill. In a study by Abushammala et al. (2014), the feedforward back-propagation MLP neural network was proposed to predict CH_4 oxidation fraction from the bottom of landfill cover soil in Malaysia. Air temperature was one of the effective input parameters in their prediction model. Possessing the ability to train time-variable relationships, time-series prediction is of special interest in GHG studies (Sergeev et al. 2018; Mohebbi et al. 2018). In a study by Mohebbi et al. (2018), the neural network auto-regressive model with exogenous inputs (NARX), a dynamic ANN model, was compared with MLP, a statistic neural network model, for predicting air carbon monoxide (CO) concentration in Shiraz, Iran. They concluded that the NARX model performed better than the MLP model. Sergeev et al. (2018) investigated the prediction ability of three neural network models of Elman neural network, MLP, and NARX to study the atmospheric CH_4 content in Arctic regions and confirmed the higher accuracy of the NARX model in their study. The NARX model was also reported to outperform other neural network and autoregression techniques in prediction of CH_4 concentrations in an atmospheric study in Russia (Buevich et al. 2020). In their study, Levenberg-Marquardt (LM) was applied for all types of ANNs as a training algorithm. In the year 2020, Fallah et al. studied the application of the multistage NARX model with LM algorithm using the climatic input parameters for CH_4 rate prediction from an urban landfill, in Regina, Canada. They reported the effectiveness and precision of the proposed technique in CH_4 gas modeling; however, the application of the periodic parameters was not assessed in their study.

Meteorological input parameters in methane prediction

Being a data-driven method, ANN performance strongly depends on input variables (Wang et al. 2015). Meteorological input parameters such as air temperature, relative humidity, air pressure, wind speed, and the effectiveness of their combination have been investigated in recent LFG modeling studies (Scozzari 2008; Li et al. 2011; Uyanik et al. 2012; Abushammala et al. 2014; Kumar et al. 2016; Xin et al. 2016). Having said that, none of these studies examined the impact of using periodic parameters and effective length of training dataset in ANN LFG prediction models.

Periodic parameter

Proper selection of input parameters with their effective combination is a major key point in ANN modeling (Arhami et al. 2013). However, applying a large number of input parameters in ANN models increases the size of the network (Maier and Dandy 2000), which lowers the processing speed and limits the network efficiency (Lachtermacher and Fuller 1994). Therefore, one can refer to the selection of the input parameters with the highest effect on model performance as the main step in ANN model development for GHG prediction studies. Using some meteorological data as inputs causes ANN models to be not much practicable for GHG forecasting since some of them are not predictable by conventional weather forecast models. In addition, climatic data are prone to stochastic fluctuations while periodic parameters are not prone to inherent variability and uncertainty (Arhami et al. 2013). Periodic parameters such as month of the year (MOY) and day of the year (DOY) have recently been used as inputs for some ANN models in atmospheric studies (Arhami et al. 2013; Khorasanizadeh et al. 2014; Gani et al. 2016; Radojević et al. 2019). Arhami et al. (2013) investigated the efficient length of training dataset and combination of climatic and periodic input variables in predicting hourly air pollutant (GHG) levels in Tehran, Iran. In their study, a stepwise procedure of eliminating the input parameter was performed to analyze the sensitivity of the prediction model to each input parameter. Khorasanizadeh et al. (2014) compared the climatic and DOY-based ANN models and reported a better performance by the DOY-based atmospheric prediction model in Birjand, Iran. In another atmospheric prediction study (global solar radiation) conducted by Gani et al. (2016), a higher accuracy of a DOY-based NARX model was reported compared to the adaptive neuro-fuzzy inference system (ANFIS) model. They also declared that using only the DOY as an input in the NARX model was a convenient approach to daily atmospheric predictions. However, in their study, finding the most efficient length of training data and forming a complete dataset was not conducted, and the interpolation method was only applied for the months with less than 5 days of missing or inaccurate values. Radojević et al. (2019) examined the usefulness of different forms of periodic parameters in combination with meteorological variables in daily ANN air pollutant prediction models in an urban area in Serbia. In their study, the significance of periodic input parameters was also evaluated using Analysis of variance (ANOVA). They reported the MOY-based ANN model proved superior to the models without MOY.

Objectives

In this study, after reducing the model uncertainty by removing the outliers and unreliable measurements and generating a complete dataset for time series ANN model, the efficient length of training input dataset was investigated to improve the LFG prediction model performance. The main goal is to provide a convenient and precise way for the daily CH_4 collection prediction by using periodic parameters as the only input of the two-stage NARX neural network without applying climatic-based variables. Periodic parameters are not prone to inherent variability and uncertainty while climatic input parameters are prone to stochastic fluctuations (Arhami et al. 2013). This study is the first to employ the periodic parameters in the NARX neural network for CH_4 prediction modeling and the objectives are as follows: (i) to assess the most efficient length of training dataset in the methane prediction model based on coefficient of determination (R^2), mean square error (MSE), and mean absolute percentage error (MAPE); (ii) to examine and compare the accuracy of the two-stage NARX model using periodic parameters along with independent and significant selected climatic input variables; and (iii) to evaluate the accuracy of a single periodic input model in methane prediction from the landfill to check if the periodic parameter can be used as the sole input in NARX landfill gas modeling.

Material and methods

Landfill of Regina

Regina landfill is located in the province of Saskatchewan, Canada. The climate of Regina is categorized as “Dfb” based on the Koppen-Geiger classification system, representing a cold climate and a warm summer (Peel et al. 2007) with a mean temperature of 3.1°C (Canada Climate Normal 2016). The landfill started its operation in 1961 and is the only municipal landfill in the city of Regina (Conestoga-Rovers & Associates 2006) with Latitude and longitude coordinates of 50° 26′ N and 104° 37′ W, respectively (Fallah et al. 2020a). LFG collection with flaring system at the landfill was stablished in July 2008, consisting of 27 vertical gas wells, and the final cover with a 1-m compacted clay layer and a 0.15-m topsoil, which was constructed in 2007 at the LFG collection area (Conestoga-Rovers & Associates 2006).

Data description

Methane collection rate

Real-time LFG data was collected at Regina landfill from August 2008 to December 2014 (Conestoga-Rovers & Associates 2008). Supervisory Control and Data Acquisition (SCADA) system measured per minute CH_4 flow using Hitech sensors, which employed wavelength infrared techniques (Conestoga-Rovers & Associates 2008). The collected LFG was composed of 44% CH_4, 37% CO_2, and 19% residual gas with the average daily CH_4 flow rate of 6100 m^3/day (4.23 m^3/min) during the period of study. A total of 1932 daily data points was measured, containing outliers and unreliable measurements among them. The methodology of the study is graphically represented in Fig. 1.

Climatic variables

Twelve climatic variables including the maximum, average and minimum daily temperature (*T*), dew point (DP), maximum and minimum daily relative humidity (*H*), air pressure (*P*), and wind speed (*W*) were collected over the study period at the Regina station (elevation 0, 50.43° N, 104.67° W) from the Weather Underground (WU, 2018). These climatic parameters were also applied in the LFG prediction studies by Scozzari (2008), Li et al. (2011), Uyanik et al. (2012), Abushammala et al. (2014), Kumar et al. (2016), and Xin et al. (2016).

Periodic parameters

Prediction of daily CH_4 data by applying the periodic input parameter as an only input would not only be appealing and

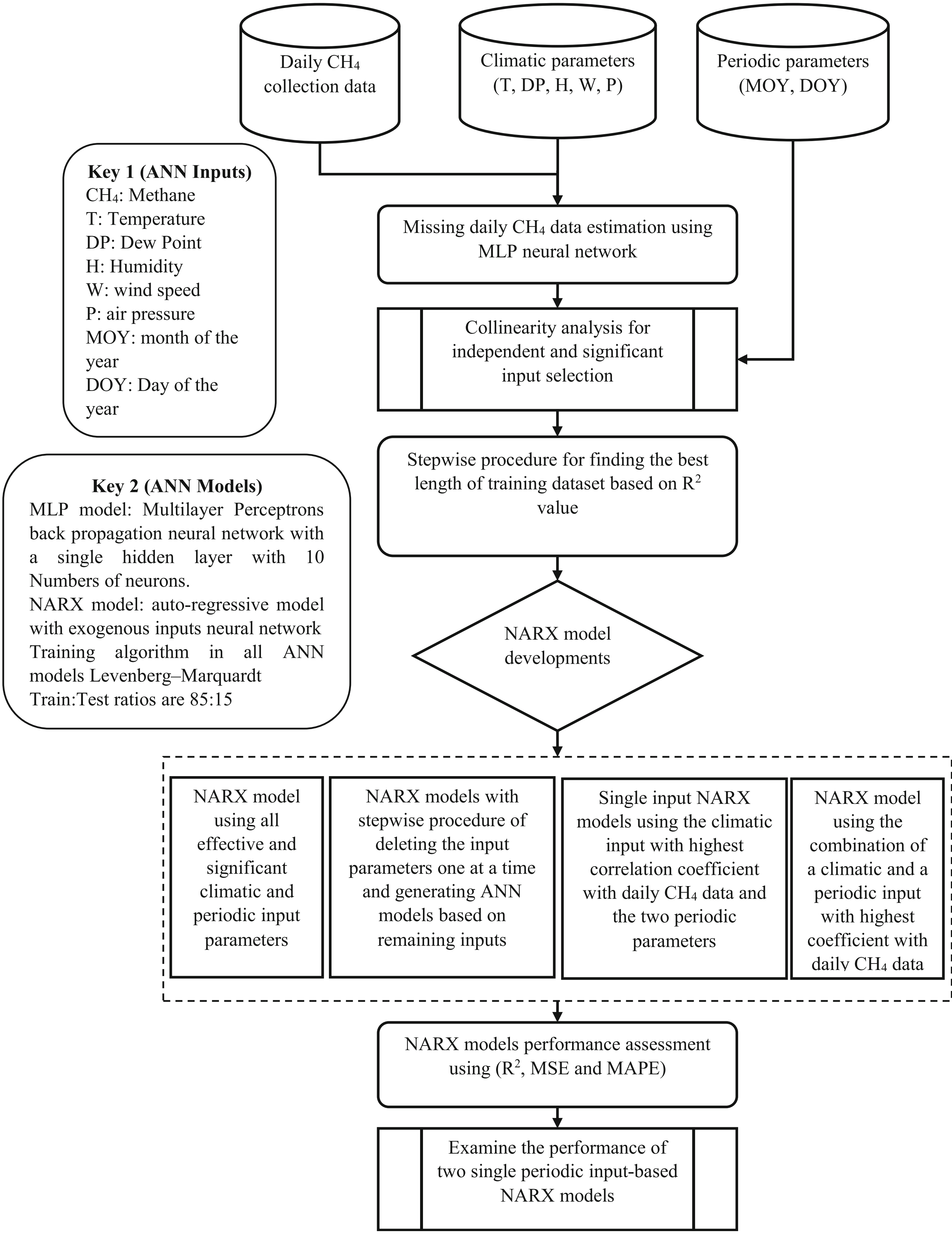


Fig. 1 Methodology flowchart

beneficial due to its simplicity and fast application but also eliminates the need for any other climatic input data and pre-calculation analysis for the climatic input. Besides the climatic parameters, time variables such as the MOY and the DOY, that indicate various frequencies in the observed data, can be employed to optimize the model outcomes. Having said that, the periodic parameters are not liable to uncertainty and substantial variations unlike some climatic parameters (Arhami et al. 2013). In this study, since the prediction of daily CH_4 collection data is the target in the ANN modeling, MOY and DOY are applied as periodic variables to represent the variation of CH_4 through the years. These periodic parameters were smoothed by applying the MOY and DOY variables through using the following equations (Arhami et al. 2013; Gani et al. 2016):

$$\mathrm{DOY} = \cos\left(\frac{2\pi d}{365}\right) \tag{1}$$

$$\mathrm{MOY} = \cos\left(\frac{2\pi m}{12}\right) \tag{2}$$

where d is day of a year, ranging from 1 to 365, and m is month of a year, ranging from 1 to 12.

Applying such types of periodic variables prevent the sudden changes in the values of day and month as input parameters, and accordingly, reduces the sudden variations in the model results and improves the model performance (Arhami et al. 2013).

Data preprocessing and missing data estimation

The existence of LFG missing data can probably be attributed to the high possibility of the frozen well heads in Regina with semi-arid cold climate, equipment failure, sensor, or maintenance problems (Fallah et al. 2020b). The CH_4 data preprocessing was performed by utilizing the collinearity analysis, filtering the outliers and missing data imputation. Pearson's correlation analysis was adapted to select the independent and significant climatic input parameters to reduce the impact of multi-collinearity by excluding the input variables that have correlation coefficients higher than 0.8 (Hamilton 1991; Adamović et al. 2018a, b; Fallah et al. 2020b) with other inputs. Fallah et al. (2020b) concluded that selection of the input variables which have no or weak correlation coefficient with other inputs reduced the errors of the CH_4 prediction models in the testing stage at the Regina landfill. Moreover, they reported that removing outliers could increase the ANN model performance at both testing and training stages. The outliers and missing data were possibly caused by system shutdowns, instruments' malfunction, maintenance work, and frozen well heads at the Regina landfill (Fallah et al. 2020b). Inter-quartile range (IQR) filtering was adapted for removing the outliers from the dataset (Kannangara et al. 2018; Fallah et al. 2020b). The data located outside of upper level = $Q_3 + \mathrm{IQR} \times 1.5$ and ower level = $Q_1 - \mathrm{IQR} \times 1.5$ were considered outliers and were excluded from the dataset (Q_1 and $Q_3$are the first and third quartiles of the dataset, respectively).

In this study, missing daily CH_4 collection data (m^3/day) was estimated by using the feed forward back propagation MLP model (Fallah et al. 2020b) with LM as the most commonly used training algorithm in ANN prediction studies (Moghaddamnia et al. 2009; Taherdangkoo et al. 2020; Buevich et al. 2020; Fallah et al. 2020b) and a default of 10 number of neurons in the hidden layer (Ozcan et al. 2006). MLP with a single hidden layer was applied by Junninen et al. (2004) for missing data estimation in the air quality datasets. The MLP with a single hidden layer has been widely applied in the air pollutant prediction studies (Elangasinghe et al. 2014; Ozkaya et al. 2007; Feng et al. 2015) and missing data estimation (Junninen et al. 2004; Dastorani et al. 2010). In this study, ANN modeling is developed in MATLAB (version 2017b). A single hidden layer was utilized to avoid overfitting problems (Kannangara et al. 2018; Singh and Satija 2018) with a sigmoid transform function and an output layer with a linear transform function. An 85:15 train:test ratio was used on the available dataset (Feng et al. 2015; Abbasi and El Hanandeh 2016; Singh and Satija 2018; Fallah et al. 2020b). One indicator of overfitting is when the model is well-fitted during the training while poorly fitted in the testing stage. In the present study, early stopping is applied to reduce the overfitting problems (Sarle 1996). Therefore, the inputs were divided into training (70%), validation (15%), and testing (15%) in all trails. In addition, over 40 trails were conducted with selected climatic and periodic parameters to assess the model accuracy and to define the model with the minimum MSE. The result from this step is the complete time series dataset (2344 daily data) in the study period (August 2008–December 2014). More details on the missing daily CH_4 data prediction is reported by Fallah et al. (2020b) and to avoid duplication has not been repeated here. Similar to Fallah et al.'s (2020) study, in this study, only the climatic input parameters have been applied for missing CH_4 data estimation.

NARX model in daily methane prediction

In the present study, to predict the daily CH_4 collection rate, a non-linear autoregressive neural network model with an external input (NARX) was employed by using the complete time series dataset produced from missing data estimation process. The standard NARX model is a two-layer network with sigmoidal and linear function in the hidden and output layers, respectively and the equations are as follows:

$$\varphi = \frac{1}{1+e^{-y}} \tag{3}$$

$$\varphi = y \tag{4}$$

The complete dataset consists of 2344 time series data points for each input-output parameter during the study period (August 2008-December 2014). In NARX models, 1992 data points (85%) were used for training and 352 data points (15%) were applied at the testing stage (Feng et al. 2015; Abbasi and El Hanandeh 2016; Singh and Satija 2018; Fallah et al. 2020b) in the time series order. Similar to the MLP model for generating the complete dataset, in the NARX models, the daily methane collection rate (m^3/day) is the target variable. In the NARX models, in addition to the climatic input parameters, the periodic parameters were also employed for model optimization assessment.

In this study, the LM training algorithm was applied in all NARX models as the most commonly used algorithm in GHG prediction studies (Fallah et al. 2020b; Buevich et al. 2020). The LM is a type of back propagation algorithm and has been applied in various ANN prediction models (Moghaddamnia et al. 2009; Taherdangkoo et al. 2020; Buevich et al. 2020; Fallah et al. 2020b) owing to the fast convergence speed (Marquardt 1963; Hagan and Menhaj 1994; Taherdangkoo et al. 2020). In LM algorithm, the weights and bias are updated based on the least-square technique (Buevich et al. 2020). The LM is a modification of the Gauss-Newton technique which consisted of consecutive approximation of the Hessian matrix to find the local optimum and optimizes the solution (Sahoo and Jha 2013; Taherdangkoo et al. 2020) using the following equation (Bishop 1995):

$$\Delta w = \left[J^T(w)\ J(w) + \lambda I\right]^{-1} J^T(w) e(w) \tag{5}$$

where w is the weight, J represents the Jacobian matrix, J^T represents the transpose matrix of J, J^TJ is the Hessian matrix, and I is the learning matrix. e is vector of network error and λ represents the step size and is automatically updated to secure the convergence according to the error at each iteration. To initiate the iteration for weight optimization in LM algorithm, the random value of λ was used in this study.

Prior to developing the ANN models, correlation analysis is usually applied to select the effective and independent inputs (Shahin et al. 2008; Fallah et al. 2020b). At this time, after calculating the periodic variables for the complete dataset, a correlation matrix was performed to identify the climatic and periodic input variables, which are statistically significant (P value < 0.05) and independent.

Stepwise procedure for the best training length

Generally, a model will be more accurate with a larger training dataset. However, the level and trend of the daily CH_4 collection rate may change over the period of time. The changes in daily CH_4 rate may be related to changes in decomposition speed of biodegradable buried waste, operational and climatic conditions in landfills. Therefore, more recent data may contribute to a better performance of the prediction model. In this study, after employing the correlation matrix, a stepwise procedure was applied to obtain the most effective length of input dataset for training the ANN models using R^2 value, the MSE, and the MAPE, between the measured and predicted daily CH_4 collection rate at the testing stage. Initially, the most recent one year of daily methane collection data were applied at the training stage and then, the temporal length of training dataset was increased gradually (6 months) until reaching the complete dataset (August 2008 to December 2014) with a training:test ratio of 85:15. Starting with the one-year-length data for training has the benefit of taking into account the full coverage of seasonal variations in CH_4 levels and climatic variables in the trained model. After identifying the most efficient length of the training dataset, a new correlation matrix was provided for comparing the coefficients of inputs in the selected lengths of training and those from considering the full dataset.

ANN models development

All independent and significant climatic and periodic parameters were applied as inputs in a NARX neural network model (first and benchmark model as shown in Fig. 1). In the second NARX group, to evaluate the sensitivity of the NARX models to each input variable, a stepwise procedure of deleting the input parameter one-at-a-time was performed and the NARX models were generated using the remaining input parameters. Moreover, in the third NARX group, single-input-based models were developed by using the only one climatic and a periodic input parameter with the highest correlation coefficient with the target variable (daily CH_4 rate). In the last NARX model, a combination of the two independent and significant climatic and periodic variables with the highest correlation coefficient with CH_4 data was constructed. The main aim of the study is to provide a precise and convenient means for predicting the daily CH_4 collection rate without applying any climatic inputs in the NARX model.

Models performance assessment

To examine the accuracy of the developed models for daily methane predictions, three statistical metrics were defined as: R^2 value, the MSE, and the MAPE. These metrics were calculated by applying the model predictions of the daily CH_4

rate and the corresponding measured data. The equations for these statistical parameters are as follows (Hastie et al. 2009):

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (O_i - P_i)^2}{\sum_{i=1}^{n} \left(O_i - \overline{O}\right)^2} \tag{6}$$

$$\mathrm{MSE} = \frac{1}{n} \sum_{i=1}^{n} (P_i - O_i)^2 \tag{7}$$

$$\mathrm{MAPE} = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{O_i - P_i}{O_i} \right| \times 100 \tag{8}$$

where O_i and P_i are the observed and predicted daily CH_4 collection values, respectively. In i = 1, 2, ..., n days, $\bar{O}$ is the mean of the observed times series daily CH_4 collection rate (m^3/day), and n is the total number of observations.

Result and discussion

Data analysis and screening

Before any preprocessing is done, 1932 time-series data points on the daily CH_4 collection rate were available (August 2008–December 2014). The fluctuations in the CH_4 collection rates and the characteristics of the daily dataset are observed in Fig. 2a and Table 1, respectively. The average daily CH_4 collection rate was 6286.87 m^3/day and close to the median (6235.77 m^3/day), which represents the normal distribution of target dataset. However, the median is higher than the average for some climatic parameters (T, DP, and H), which indicates the data to be skewed. The most fluctuated parameters are T and DP (Max, Avg, and Min) with coefficients of variation higher than 1 (1.43, 3.21, −6.76, 4.41, −11.80, and −2.70). This may be related to the extreme cold winters in the study area. A close-to-one coefficient of variation (0.94) for the minimum wind speed shows the considerable variations of this input parameter. The coefficient of variation of the air pressure is close to zero (0.01) in the study period.

Preprocessing for missing data imputation

Collinearity analysis

The preprocessing and missing data estimation procedure is similar to the study conducted by Fallah et al. (2020b), this time for CH_4 collection rate prediction at the Regina landfill. In this study, the correlation analysis indicates that T_{avg} has the greatest correlation coefficient (R = 0.29) with the daily CH_4 collection rate. High correlation coefficients, ranging from 0.92 to 0.99, are observed between T (Max, Avg, and Min) and DP (Max, Avg and Min). W_{Max} and W_{Min}; P_{Max} and P_{Min} are also correlated to each other with R values of 0.85 and 0.83, respectively, which are above the 0.8 cut-off value (Hamilton 1991; Adamović et al. 2018a, b). Therefore, to avoid multicollinearity that may result in confusion in ANN modeling, and to increase the accuracy of the MLP missing data estimation model (Fallah et al. 2020b), the combination of the average air temperature (T_{avg}), maximum pressure (P_{Max}), minimum humidity (H_{Min}), maximum wind speed (W_{Max}), and maximum humidity (H_{Max}) with correlation coefficients of 0.29, −0.15, −0.11, −0.06, and −0.05, respectively, have been applied as independent and significant (P value < 0.05) input variables in the ANN modeling.

Removal of outliers

Among 1932 CH_4 observed data points, errors, and outliers are removed using the inter-quartile range (IQR = 1007 m^3/day, Q1 = 5760 m^3/day, and Q3 = 6768 m^3/day). The CH_4 collection rate data smaller than lower level = 4250 and higher than upper level = 8278 were excluded from the dataset. In the dataset, 2.5 % of CH_4 data were below the lower level while no data was higher than the upper level. After performing correlation analysis and the removal of outliers, the remaining 1883 data points were applied in the MLP neural network model described in section 2.3 to estimate the missing daily CH_4 collection rate.

Missing data estimation

To form a complete time series dataset, 2344 daily CH_4 data points are expected in the study period (from August 2008 to December 2014) while only 1883 data points are available after the outlier removal. Therefore, 19.7% of CH_4 collection data are missing, and are predicted through the back propagation MLP neural network model. In this model, the available data points (1883) were divided into two groups of 85% and 15%, in which the 85% were used at the training and the remaining 15% were employed at the testing stage to predict the missing data. Therefore, a train: test ratio of 65:35 was applied to the incomplete dataset (85:15 to the available dataset) and the missing daily CH_4 rate data were predicted in the testing stage using the MLP model. The model shows an acceptable performance with the average MAPE of 7.97% and 9.15% at the training and testing stages, respectively. The 461 daily CH_4 rate predicted data were generated from the testing stage of the MLP model led to obtaining a complete dataset (as illustrated in Fig. 2b) consisting of 2344 data points in the study period (from August 2008 to December 2014). In construction of the complete dataset, to minimize the effect of the MLP prediction model errors, only the missing data were replaced by the testing stage outcomes (constructed data) while the observed data were not replaced by the predicted ones. The complete dataset was employed in the NARX neural

Table 1 Statistics of the daily dataset (August 2008 to December 2014)

	Max	Mean	Median	Min	St. deviation	St. deviation/ mean
(Output variable)[a]						
CH_4 collection rate (m^3/day)	7910.87	6286.87	6235.77	4299.41	619.99	0.10
(Input variable)[b]						
T_{Max} (°C)	35	9.8	11.67	−28.89	14.01	1.43
T_{Mean} (°C)	26.67	4.04	6.67	−32.78	13	3.21
T_{Min} (°C)	21.67	−1.83	0.56	−40	12.37	−6.76
DP_{Max} (°C)	25	2.52	3.89	−33.89	11.1	4.41
DP_{Mean} (°C)	22.78	−1	0	−37.78	11.76	−11.8
DP_{Min} (°C)	20	−4.72	−2.78	−45	12.73	−2.7
H_{Max} (%)	100	89.15	93	54	8.66	0.1
H_{Min} (%)	93	52.4	53	7	18.95	0.36
W_{Max} (km/h)	74.03	32.23	32.19	9.66	11.05	0.34
W_{Min} (km/h)	37.01	6.36	6.44	0	5.97	0.94
P_{Max} (inHg)	31.07	30.12	30.1	29.3	0.25	0.01
P_{Min} (inHg)	30.8	29.88	29.88	29.08	0.25	0.01

T, air temperature; *DP*, dew point; *H*, humidity; *W*, wind speed; *P*, sea-level pressure

[a] Output variable: the source for CH_4 collection rate (m^3 /day) is Conestoga-Rovers and Associates (2008)

[b] Input variable source is WU 2019. Weather data for Regina, Saskatchewan (Station information: Elevation 0, 50.43° N, 104.67° W). (https://www.wunderground.com/history/monthly/ca/regina/CYQR/date/2019-4?cm_ven=localwx_history)

network model developments in which, 1992 data points (85%) were used at training whereas 352 data points (15%) were applied at the testing stage in time series order.

Preprocessing for NARX models developments

Correlation analysis for complete dataset

Effective selection of input variables, reducing the uncertainty of model inputs, and improving the prediction model performance are essential to the practical use of prediction models (Arhami et al. 2013). As described in the methodology, in developing the NARX neural network models, periodic variables are also applied in addition to the climatic parameters. The results from the correlation analysis to find the most effective and independent input parameters in the NARX prediction models are tabulated in Table 2.

Similar to the correlation analysis for the missing data estimation, in a complete dataset, T_{Avg} showed the highest correlation (0.312) with the daily CH_4 collection rate. The input parameters with correlation coefficients less than |0.099| were not used as input in ANN modeling due to their minimal impacts on daily CH_4 rate. Multicollinearity is observed between *T* and DP (Max, Avg, and Min) with high correlation coefficients ranging from 0.928 to 0.987. P_{Min} is correlated with P_{Max} with the *R* value of 0.827 higher than the cut off value (0.8) (Hamilton 1991; Adamović et al. 2018a, b). As discussed in the methodology section, the periodic input parameters including MOY and DOY were considered in the analysis to evaluate the effectiveness of the periodic parameters on CH_4 rate prediction models. Based on the correlation matrix, MOY and DOY variables are highly correlated to each other (R = 0.954) and collinearity is also observed between DOY and T (Max, Avg, and Min) with the absolute *R* value ranging from 0.837 to 0.853. Therefore, to decrease the collinearity problems that may cause confusion in the ANN modeling, the combination of the average air temperature (T_{Avg}), maximum pressure (P_{Max}), minimum humidity (H_{Min}), and only MOY was employed as the independent and significant (P value < 0.05) input variables in ANN model developments. However, DOY was applied in a single-input-variable ANN model, to check the effectiveness of the periodic parameters on the accuracy of CH_4 prediction models. Information on different ANN CH_4 prediction models is provided in the Result and discussion section.

Stepwise procedure for the best training length

As described in the methodology section, initially, the most recent 1 year of measured data was utilized for training. Then, the temporal length of training data was gradually increased by 6 months at each step until reaching the complete dataset in which the daily CH_4 rate data from 01 Aug 2008 to 13 Jan 2014 and from 14 Jan 2014 to 30 Dec 2014 were applied

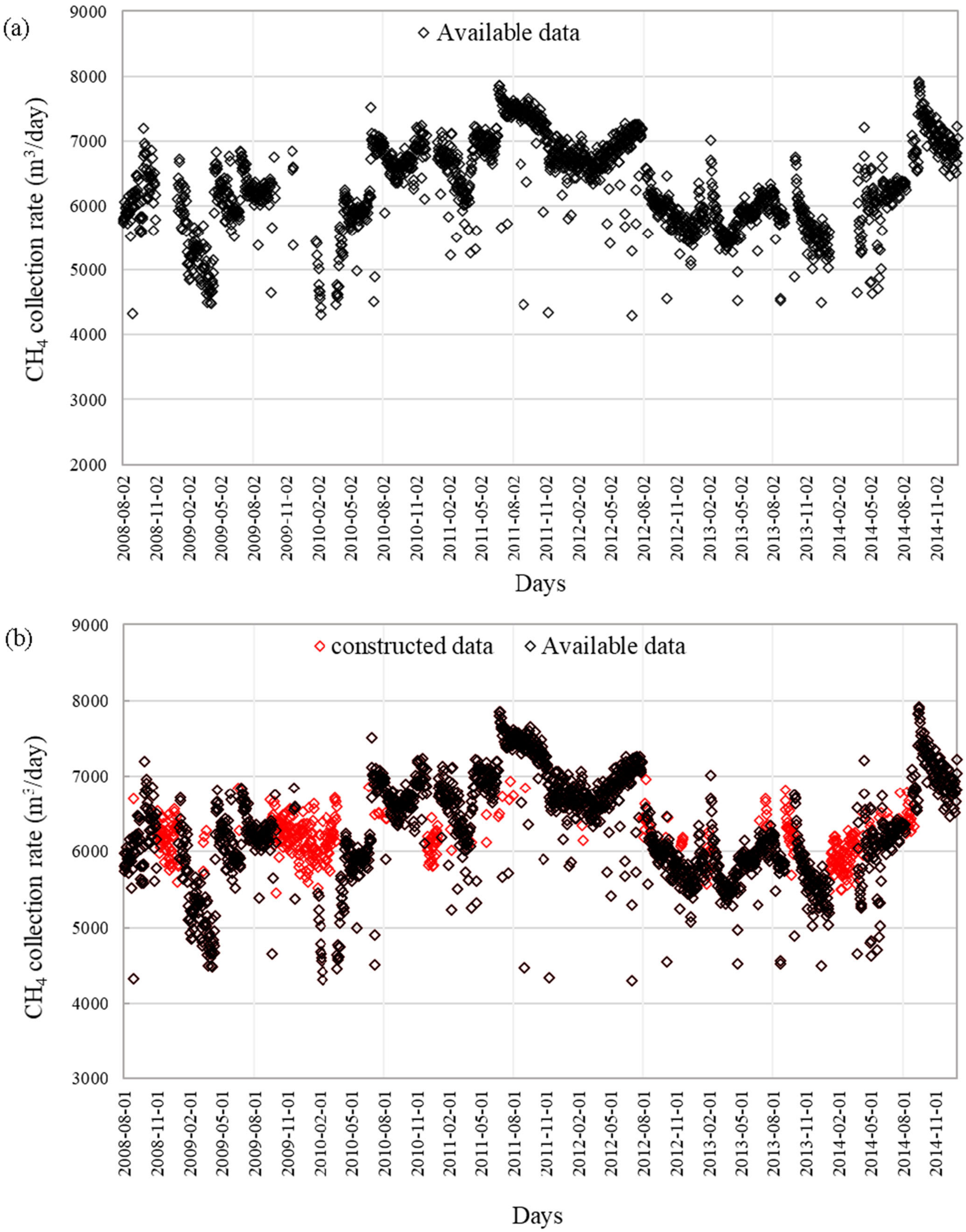


Fig. 2 Missing data estimation using MLP neural network; **a** measured CH_4 data in the study period; **b** constructed missing data to form a complete daily CH_4 dataset

Table 2 Correlation matrix of daily CH_4 collection rate and input variables (August 2008 to December 2014)

	CH_4 collection rate (m^3/day)	T_{Max} (°C)	T_{Avg} (°C)	T_{Min} (°C)	DP_{Max} (°C)	DP_{Avg} (°C)	DP_{Min} (°C)	H_{Max} (%)	H_{Min} (%)	W_{Max} (kph)	W_{Min} (kph)	P_{Max} (inHg)	P_{Min} (inHg)	MOY	DOY
CH_4 collection rate (m^3/day)	1.000														
T_{Max} (°C)	0.307	1.000													
T_{Avg} (°C)	0.312	0.987	1.000												
T_{Min} (°C)	0.310	0.942	0.984	1.000											
DP_{Max} (°C)	0.299	0.952	0.969	0.958	1.000										
DP_{Avg} (°C)	0.306	0.944	0.976	0.980	0.987	1.000									
DP_{Min} (°C)	0.306	0.928	0.970	0.987	0.964	0.990	1.000								
H_{Max} (%)	−0.043	0.208	0.245	0.277	0.400	0.396	0.374	1.000							
H_{Min} (%)	−0.140	−0.635	−0.564	−0.468	−0.413	−0.397	−0.392	0.308	1.000						
W_{Max} (kph)	−0.052	0.007	0.026	0.041	0.044	0.017	0.005	−0.045	0.016	1.000					
W_{Min} (kph)	−0.052	−0.081	−0.049	−0.013	−0.065	−0.055	−0.038	−0.145	0.088	0.463	1.000				
P_{Max} (inHg)	−0.162	−0.529	−0.561	−0.580	−0.583	−0.587	−0.581	−0.242	0.129	−0.151	−0.009	1.000			
P_{Min} (inHg)	−0.124	−0.371	−0.387	−0.391	−0.443	−0.417	−0.390	−0.206	0.019	−0.377	−0.108	0.827	1.000		
MOY	−0.099	−0.724	−0.739	−0.735	−0.707	−0.714	−0.712	−0.126	0.485	−0.002	0.055	0.339	0.150	1.000	
DOY	−0.185	−0.837	−0.853	−0.845	−0.819	−0.828	−0.827	−0.174	0.549	0.020	0.073	0.373	0.171	0.954	1.000

at the training and testing stages, respectively. Performance metrics (R^2 value, MSE, and MAPE) for predicted and available CH_4 levels with various volumes of training data are illustrated in Fig. 3. The best fit with the highest average R^2 value of 0.8 and the lowest average MSE and MAPE of 47,698.30 m^3/day and 2.26% at the testing stage, respectively, was achieved by applying the most recent 3 years of available data (from 10 Jul 2011 to 23 Jun 2014) for training (data from 24 Jun 2014 to 31 Dec 2014 were used for testing). In comparison to the full-length dataset, the average R^2 value increased from 0.72 to 0.80 and MSE and MAPE decreased from 97,918.39 to 47,698.30 and from 3.10 to 2.26%, respectively, during the testing stage. This result may possibly be attributed to the fluctuations of daily CH_4 rate data over the past years and the date 22 Jun 2011 with the peak CH_4 rate of 7852.945 m^3/day.

As previously described, after identifying the most efficient length of training dataset, a comparative analysis was performed to see the changes in the coefficients of the effective inputs between 3-year length training dataset and those of in the trained model with the full dataset. The coefficients of inputs for 3-year length data and the full dataset is tabulated in Table 3. The result shows that by applying the 3-year length data in training, the coefficients of T_{Avg} and P_{Max} and H_{Min} increased by 10.56%, 18.24%, and 2.83%, respectively, and T_{Avg} is still the highest correlated (R = 0.345) input among other input parameters.

NARX models performance assessment

A total of nine time series ANN prediction models were developed using the most recent 3 years of data for training. The first ANN model was constructed with the combination of 4 inputs (*T*-*P*-*H*-MOY), and four ANN models were developed through sensitivity analysis using the stepwise procedure of omitting one input at the time (without *T*, without *P*, without *H*, without MOY). Moreover, single-input models were generated by using *T* (with highest correlation coefficient with target variable), MOY, DOY (the two periodic parameters), and the last model (*T*-MOY) performed by a combination of the climatic and periodic inputs with highest coefficient with target variable. The comparative evaluation of these nine time-series ANN model performances is presented in Fig. 4.

MSE is scale dependent; therefore, the R^2 value and MAPE at the testing step are used to compare the relative performance of the time series ANN models. The MAPE of the nine CH_4 prediction models compared favorably to other solid waste energy recovery ANN models, in which MAPE ranged from 0.3 to 12.6% (Ogwueleka and Ogwueleka 2010; Nabavi-Pelesaraei et al. 2017; Adamović et al. 2018a, b; Fallah et al. 2020b) as shown in Appendix Table 4.

The model with all four independent and significant inputs performed well with an average R^2 value of 0.829 and the average MSE and MAPE of 40,839.68 m^3/day and 2.05%, respectively, at the testing stage. Among the ANN groups generated by sensitivity analysis, the model with three inputs

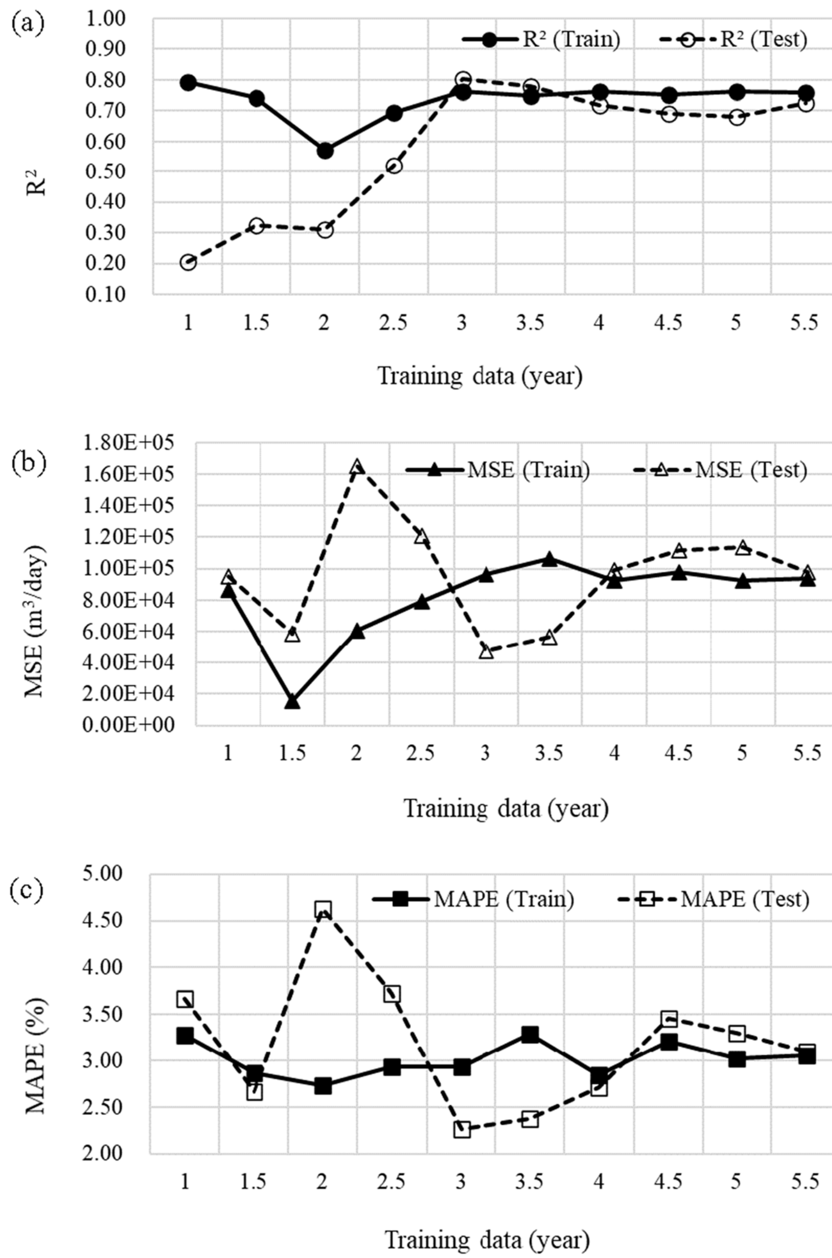
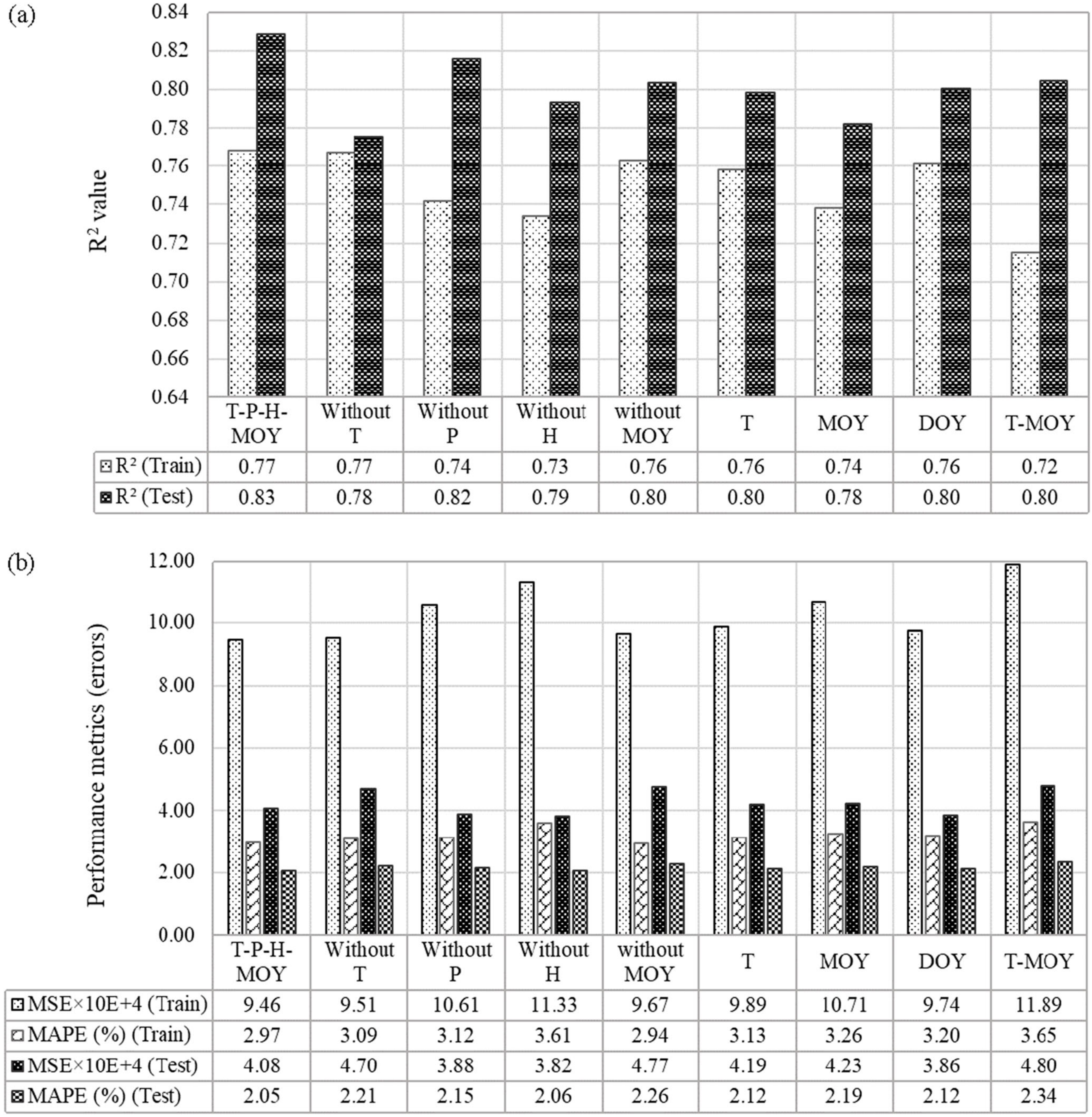


Fig. 3 Performance metrics (R^2 value, MSE, and MAPE) for predicted and measured CH_4 levels, with various volume of training dataset

Table 3 Comparison of inputs coefficients; full dataset (from 01 Aug 2008 to 31 Dec 2014) and 3-year length training dataset (from 10 Jul 2011 to 31 Dec 2014)

	CH_4 collection rate (m^3/day)	T_{Avg} (°C)	P_{Max} (inHg)	H_{Min} (%)
Full dataset (from 01 Aug 2008 to 31 Dec 2014)				
CH_4 collection rate (m^3/day)	1			
T_{Avg} (°C)	0.312	1		
P_{Max} (inHg)	−0.162	−0.561	1	
H_{Min} (%)	−0.140	−0.564	0.129	1
3-year length training dataset (from 10 Jul 2011 to 31 Dec 2014)				
CH_4 Collection rate (m^3/day)	1			
T_{Avg} (°C)	0.345	1		
P_{Max} (inHg)	−0.191	−0.541	1	
H_{Min} (%)	−0.144	−0.586	0.131	1



	T-P-H-MOY	Without T	Without P	Without H	without MOY	T	MOY	DOY	T-MOY
R^2 (Train)	0.77	0.77	0.74	0.73	0.76	0.76	0.74	0.76	0.72
R^2 (Test)	0.83	0.78	0.82	0.79	0.80	0.80	0.78	0.80	0.80

	T-P-H-MOY	Without T	Without P	Without H	without MOY	T	MOY	DOY	T-MOY
MSE×10E+4 (Train)	9.46	9.51	10.61	11.33	9.67	9.89	10.71	9.74	11.89
MAPE (%) (Train)	2.97	3.09	3.12	3.61	2.94	3.13	3.26	3.20	3.65
MSE×10E+4 (Test)	4.08	4.70	3.88	3.82	4.77	4.19	4.23	3.86	4.80
MAPE (%) (Test)	2.05	2.21	2.15	2.06	2.26	2.12	2.19	2.12	2.34

Fig. 4 Comparative evaluation of the nine-time series daily CH_4 prediction models using performance indices

(without *H*) showed the lowest average MSE of 38,171.21 m^3/day and MAPE of 2.06% with the R^2 value of 0.793. The results, however, highlight the importance of periodic parameters on the accuracy of CH_4 collection prediction models. Of these four models with three inputs as shown in Fig. 4, Without MOY model had the poorest estimates with a MSE of 47,698.30 m^3/day and a MAPE of 2.26%. It also implies that MOY is an acceptable indicator for CH_4 rate prediction models. The second poorest model was without *T* model with a MSE of 47,037.12 m^3/day and MAPE of 2.21% but with lower R^2 value of 0.775 than that of the without MOY model (0.803). Among all the three single-input variable models, the DOY-based model had the highest R^2 value of 0.801 and the lowest MSE of 38,579.24 m^3/day. The MAPE in *T* and DOY models are both 2.12%, and negligibly lower than that of the MOY-based model (2.19%). The last model (*T*-MOY) did not show a high performance in comparison to the other eight ANN models, with the highest MSE and MAPE of 48,033.75 and 2.34%, respectively. Therefore, the combination of these two climatic and periodic parameters is not

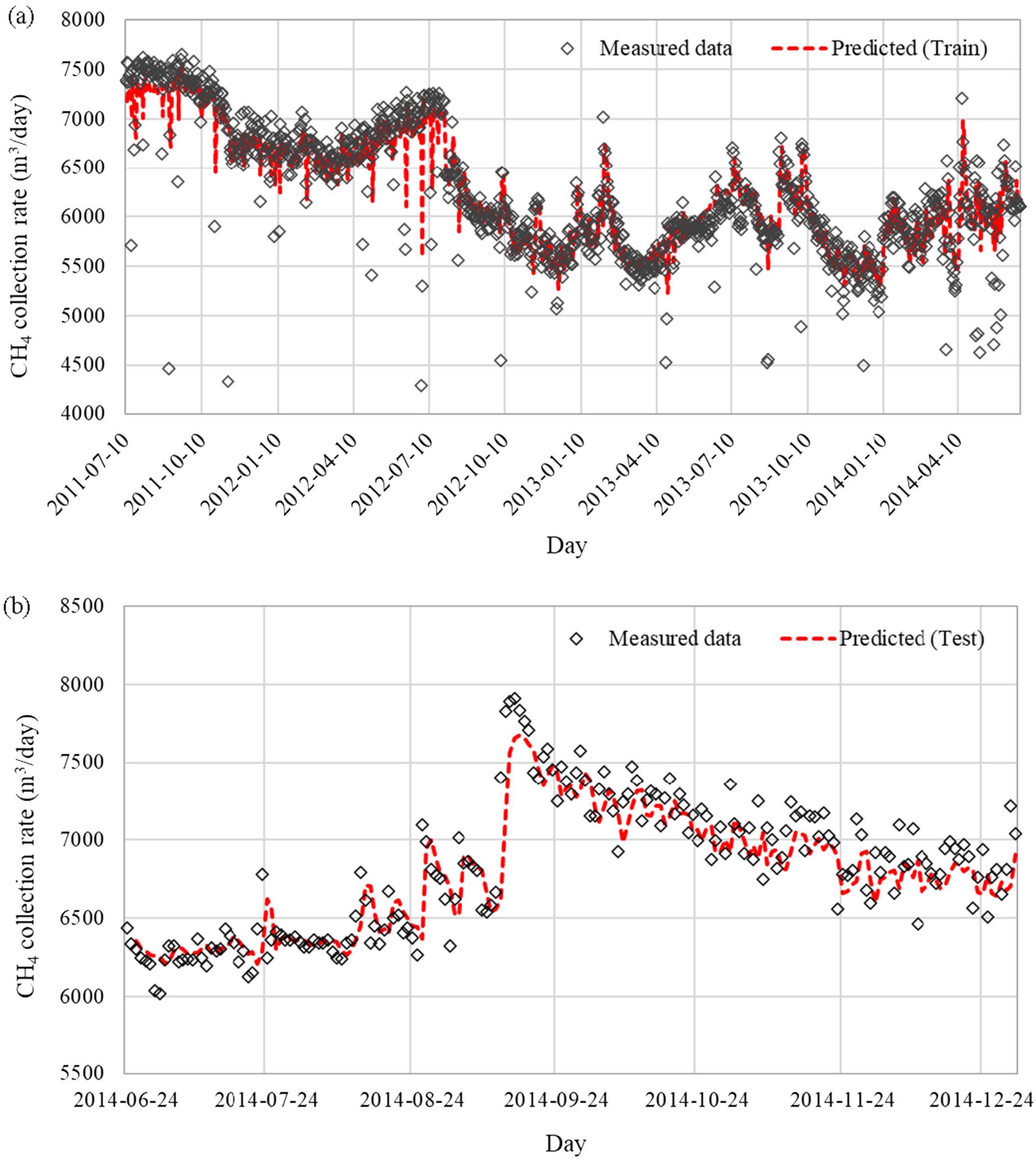


Fig. 5 Performance of the day of the year (DOY)-based CH_4 prediction model; **a** training stage from 10 Jul 2011 to 23 Jun 2014; **b** testing stage from 24 Jun 2014 to 31 Dec 2014

recommended in this study. Comparison of the two single periodic input variable models shows the higher performance of DOY than that of the MOY model with respect to all three performance indices: R^2, MSE, and MAPE of the DOY model are 2.37%, 8.69%, and 3.17% better than those in the MOY model, respectively. The DOY model even performed better than the *T* model with 7.95% lower MSE, which represents the benefit of considering DOY as the only input in CH_4 rate prediction models from the landfill.

The R^2 value and MAPE of the DOY model (0.80 and 2.12%, respectively) at the testing stage are compared favorably to other published ANN models (Ozcan et al. 2006;

Ozkaya et al. 2007; Karacan 2008; Ogwueleka and Ogwueleka 2010; Nabavi-Pelesaraei et al. 2017; Adamović et al. 2018a, b), in which the R^2 value and MAPE ranged from 0.66 to 0.0.99 and 0.3 to 12.6%, respectively (Appendix Table 4). It is observed that the performance of the DOY-based model with MAPE of 2.12% is obviously higher than those reported in Ogwueleka and Ogwueleka (2010) and Adamović et al. (2018a, b) studies in which the MAPE ranged from 9.05 to 12.6%. The results from the present study suggest that applying DOY as a single input of time-series ANN models can be a convenient and rapid approach for daily CH_4 rate prediction from landfills, particularly for the landfills with no reliable climatic data.

Using the DOY model, the measured and predicted daily CH_4 collection data are graphically compared in Fig. 5 at both training and testing stages. Figure 5a shows the DOY model in training period from 10 Jul 2011 to 23 Jun 2014. The DOY model well captured the daily CH_4 collection data particularly the day with average and peak values. Figure 5b represents the DOY model in the testing stage from 24 Jun 2014 to 31 Dec 2014. This model again accurately captured the real CH_4 collection data at the testing period. The model, however, is less useful in the prediction of the CH_4 data with values lower than the daily average CH_4 collection rate.

Conclusion

Accurate and precise LFG prediction models are not only essential for mitigating the GHG environmental impacts but also helpful in the efficient LFG management systems in landfills. The preprocessing steps, including minimizing multicollinearity problems, filtering the outliers and erroneousness, and constructing missing data to form a complete dataset, were employed on the raw daily CH_4 collection data. Missing data estimation using the MLP neural network model represented an acceptable performance at both training (MAPE = 7.97%) and testing (MAPE = 9.15%) stages. In this study, the CH_4 rate prediction model performance was improved by selecting the most recent 3-year length dataset for training through the stepwise procedure. It is found that using the most recent 3-year length training dataset, the R^2 value increased by 10.86% while the MSE and MAPE decreased by 51.29% and 26.97%, respectively, at testing stages.

Proper selection of input parameters and model architecture is a key item in ANN model developments. In the present study, a fast and convenient approach for the methane rate prediction model was investigated based on periodic parameters as a sole input. In all nine NARX daily CH_4 models developed in this study, the R^2 value, MSE, and MAPE of the models are in ranges of 0.775–0.829, 38,171.21–48,033.75 m^3/day, and 2.05–2.34%, respectively. Among all nine ANN models, the *T-P-H*-MOY model with all independent and significant climatic and periodic inputs represented the highest performance with R^2 value and MAPE of 0.829 and 2.05%, respectively, with an MSE of 40,839.68 m^3/day at the testing stage. The sensitivity analysis showed that MOY plays an important role in daily CH_4 rate prediction models since by eliminating MOY, the model's accuracy R^2, MSE, and MAPE dropped by 3.07%, 16.79%, and 10.25%, respectively (at testing stage). A favorable precision is achieved by the DOY model with an R^2 value of 0.80, MSE of 38,579.24 m^3/day, and MAPE of 2.12%, respectively. The results suggest that the highest accuracy is achieved by the model with all four independent and significant climatic and periodic inputs. However, application of the DOY as the only input in the NARX CH_4 prediction models has minimum impacts on the prediction accuracy of the model with four climatic and periodic inputs by reducing the R^2 value by 3.41% and increasing MAPE by 3.07%.

The results illustrate utilizing both MOY and DOY as sole inputs in the daily CH_4 rate prediction models would be highly practical owing to the precise performance of the time series ANN models. In this study, the DOY-based model outperforms the MOY-based model, probably due to the greater absolute coefficient of DOY ($|R| = 0.185$) than that of MOY ($|R| = 0.099$) with the daily CH_4 collection rate data in the correlation matrix. The main advantage of the DOY-based NARX model application is its simplicity and no need for meteorological input elements. The results suggest that the DOY-based model can be applied as proper substitutes for climatic-based NARX CH_4 prediction models owing to their close and precise prediction. Therefore, the proposed method can be applied as an effective and convenient LFG modeling tool, particularly in landfills with no climatic data.

Appendix 1

Table 4 Comparison of the DOY-based ANN model performance with other municipal solid waste energy recovery ANN models at the testing stage

Studies	R^2	MAPE (%)
Ozcan et al. (2006)	0.66	NR*
Ozkaya et al. (2007)	0.92	NR
Karacan (2008)	0.85	NR
Qdais et al. (2010)	0.86	NR
Ogwueleka and Ogwueleka (2010)	0.96	9.6
Abushammala et al. (2014)	0.88	NR
Nabavi-Pelesaraei et al. (2017)	0.86–0.96	2.1–0.3
Adamovic et al. (2018a)	0.99	7.76
Adamovic et al. (2018b)	0.92–0.98	9.05–12.6
The present study	0.80	2.12

NR, not reported

Abbreviations *ANN,* Artificial neural network; *CH4,* Methane; CO_2, Carbon dioxide; *DOY,* Day of the year; *DPMax,* Maximum dew point; *DPMean,* Mean dew point; *DPMin,* Minimum dew point; *GHG,* Greenhouse gas; H_{Max}, Maximum relative humidity; H_{Min}, Minimum relative humidity; *IA,* Index of agreement; *IQR,* Inter-quartile range; *LFG,* Landfill gas; *LM,* Levenberg-Marquardt; *MAPE,* Mean absolute percentage error; *MLP,* Multilayer perceptrons; *MOY,* Month of the year; *MSE,* Mean square error; *NARX,* Non-linear auto-regressive model with exogenous inputs; P_{Max}, Maximum air pressure; P_{Min}, Minimum air pressure; *Q1,* First quartiles; *Q3,* Third quartiles; *R,* Correlation coefficient; R^2, Coefficient of determination; *RMSE,* Root mean square error; *SCADA,* Supervisory Control and Data Acquisition; T_{Max}, Maximum temperature; T_{Mean}, Mean temperature; T_{Min}, Minimum temperature; W_{Max}, Maximum wind speed; W_{Min}, Minimum wind speed

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Author contributions Bahareh Fallah: Conceptualization, Formal analysis, Writing and Original draft preparation. Farshid Torabi: Supervision, Review & Editing.

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Data availability The data that support the findings of this study are available from City of Regina Solid Waste Department but restrictions apply to the availability of these data, which were used under license for the current study, and so are not publicly available. Data are however available from the authors upon reasonable request and with permission of City of Regina Solid Waste Department.

Declaration

Competing interests 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.

Ethics approval and consent to participate Not applicable

Consent for publication Not applicable

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