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ORIGINAL RESEARCH PAPER

Application of artificial neural networks for predictive model of municipal solid waste collection in tourist cities

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ABSTRACT

BACKGROUND AND OBJECTIVES: Tourism is a critical component of the economic framework in Thailand and numerous other countries worldwide, acting as a significant revenue generator. In the year 2022, the tourism industry made a significant contribution to Thailand's Gross Domestic Product, representing 22.92 percent of the total. However, the emphasis on urban development and management in order to boost visitor numbers can worsen urban metabolism, leading to an escalation in resource. The urban administration needs to know how much waste must be managed to plan for effective environmental and public health management. The focus of this study is on the construction of an artificial neural network forecasting model that takes into account socioeconomic and demographic variables to anticipate the management of municipal solid waste in a city known for tourism.

METHODS: Models were generated by synthesizing and integrating municipal solid waste collection quantities with 17 inputs of socioeconomic, demographic, event occurrences, and tourism-specific metrics variables from 2015-2021 in Chiang Mai municipality. Deep learning techniques were used to create the models. Socioeconomic characteristics were derived using nosecount data at the provincial and municipal levels. Data preprocessing involved the implementation of knowledge discovery in database strategy to ensure the creation of datasets with sufficient numbers and quality for modeling. This issue involved calculating the correlation coefficient between 17 inputs and the quantities of municipal solid waste collected. RapidMiner® computer software was used to construct a model incorporating frameworks using artificial neural network techniques. To ensure robustness and prevent overfitting, the dataset was divided into training and validation sets. The model was trained using backpropagation methods, and the evaluation of the model's performance was based on the correlation between the observed and predicted values of the mean municipal solid waste collection rate.

FINDINGS: The waste prediction model achieved optimal performance by incorporating eight input variables across two hidden layers, one consisting of ten nodes and the other of five nodes. Across eight trials, this arrangement produced the lowest correlation coefficient (0.67), mean absolute error (320.779 +/- 22.080), and root mean square error (16.5). On the other hand, the chosen model used 17 input variables split across two hidden layers, each with 8 or 4 nodes. The model yielded a correlation coefficient of 0.69, a mean absolute error of 461.953 +/- 706.680, and a root mean square error of 21.9. The current daily amount of municipal solid waste collected is 340 metric tonnes, while the projection model anticipates an increase to 348 metric tonnes per day by 2023, with a margin of error of 2 percent. The model further predicts a daily garbage collection of 361 metric tons through 2030.

CONCLUSION: Future waste management strategies may be planned, and various environmental impacts in tourism cities can be analyzed using the forecasting process and framework for the municipal solid waste collection rate described in this research. These characteristics are harnessed by the model to gain a thorough insight into waste dynamics in metropolitan regions with high tourist activity, ultimately facilitating the adoption of more sustainable urban planning and management approaches.

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INTRODUCTION

Over the past few decades, tourism has risen to become a key and powerful sector in the economies of various countries. Despite the coronavirus disease 2019 caused by Coronavirus disease (SARS-COVID-19) breakout in 2021-2022, there will still be a period of swift recuperation. The global gross domestic product (GDP) is comprised of 7.6-9.2 percent (%) from the tourism sector in 2022-2023 (Statista Research Department, 2023). Prior to the SARS-COVID-19 pandemic, tourism held the distinction of being the largest service industry globally. Approximately 10% of global employment, close to 7% of total global trade, and a quarter of the world's service exports were attributed to the tourism sector (The World Bank, 2022). While tourism can provide significant economic opportunities, the effect also has negative environmental repercussions that raise public health concerns (UNEP, 2021). The increase in tourist numbers during peak seasons has a significant impact on the generation of municipal solid waste (MSW), leading to a notable rise in waste production (Sharma, 2016). Conversion to alternative or value-added products is one strategy for mitigating the environmental and health effects of sources-generated waste action from a sustainability standpoint (Koliotasi *et al.*, 2023). Several authorities have enacted policies to incentivize the conversion of city waste into environmentally sustainable materials or finished products. Many of these policies concentrate on waste separation, plastic ban, green fertilizers, bioelectricity, biofuels, or adsorbents (PCD, 2023). The precise estimates of the generation rate and composition of MSW from the tourism sector are crucial for ensuring sustainable management and reutilization of MSW. Striving for exact MSW predictions and assessments may present considerable challenges for waste management systems and the environment. Potential problems could involve superfluous regulations, heightened ecological consequences, and insufficient or exaggerated waste management facility capabilities. Inefficient waste disposal infrastructure can lead to serious health risks. Inadequately planned, managed, and operated recycling and incinerator operations specifically lead to air pollution and disease spread. Thailand struggles to transition to zero waste management to meet sustainable development goals (SDGs) and establish a circular economy (PCD, 2023). The forecasting of MSW generation serves decision-makers and policymakers to anticipate future needs and select appropriate MSW treatment systems. It is imperative to make precise predictions in order to formulate a sustainable waste management plan that caters to the needs of the community or the entire nation (Pudcha *et al*., 2023). The development of big data processing and analysis in recent years has encouraged scholars to investigate ways to draw more pertinent conclusions from the massive volumes of data gathered in technical operations, research, monitoring, statistics, and other fields. Various data analysis and modeling techniques have been utilized in the field of environmental engineering and research to address environmental issues. Numerous forecasting techniques, including multiple linear regression (MLR) (Azadi and Karimi-Jashni, 2016; Golbaz *et al*., 2019), principal component analysis (PCA) (Minoglou and Komilis, 2018), response surface method (RSM) (Gopal *et al.*, 2021; Shamshiry *et al.*, 2014) and grey model (Pudcha *et al.*, 2023) have been extensively used in pollution control, technical optimization, and municipal waste management. Demonstrating nonlinearity, time variation, multiple sources, and diverse targets can be achieved by addressing additional considerations. The shortcomings of these analytic techniques lie in their inability to identify correlations, optimize control parameters, and enhance systematic performance. Artificial intelligence (AI) techniques have rapidly progressed and are being applied in various industries in recent years. These strategies imitate human capabilities such as problem-solving, acquiring knowledge, perception, understanding, logical thinking, and environmental awareness (Dwivedi *et al.*, 2021). Artificial neural networks (ANN) are a widely recognized AI technology, known for their ability to process large amounts of data, identify non-linear relationships, and generate accurate (Mijwil, 2021). ANNs have been extensively utilized in various sectors like agriculture (Dwivedi *et al.*, 2021), disaster (Dechkamfoo *et al.*, 2022; Ohanuba *et al.*,2023), finance (Musleh Al-Sartawi *et al.*, 2022), management (Tochaiwat *et al.*, 2023), medical (Shahid *et al.*, 2019) and engineering (Adda *et al.*, 2022; Choi *et al*., 2020; Liu *et al*., 2021; Salehi and Sigit Lestari, 2021). By leveraging the powerful self-learning capabilities and accuracy of ANNs, this approach replicates the intricate connection between

input and output data without requiring extensive mathematical calculations ANNs have been used in the field of environmental engineering to address a variety of issues, such as air pollution (Elangasinghe *et al.*, 2014), water and wastewater treatment (Alsulaili and Refaie, 2020; Choi *et al.*, 2020), ground water contamination (Park *et al.*, 2024; Stylianoudaki *et al.*, 2022) and also solid waste management (Xu *et al.*, 2021). Kontokosta *et al.* (2018) showed that by estimating daily and weekly building-level waste and recycling in New York City. The accuracy of residential waste predictions is significantly improved with the use of ANN models, boasting mean absolute error (MAE) values under 20% and high R-squared values of 0.87. Kannangara *et al.* (2018) developed predictive models for estimating municipal solid waste (MSW) production in Canada by utilizing socioeconomic and demographic information. The models predicted MSW generation with a 16–23% prediction error. MLR models were produced by Abdulredha *et al*. (2018) during large-scale celebrations in Kerbala, Iraq. The models demonstrated a high level of accuracy in predicting the amount of solid waste generation (SWG) from hotels, achieving R-squared values of 0.799 and projecting an average SWG rate of 0.89 per guest per day. Mateu-Sbert *et al.* (2013) also calculated the influence of Menorca Island, Spain's tourist population, on MSW. Nevertheless, no variables essential for constructing an MSW collection model for a tourism city have been discovered in the research conducted. Consequently, this research aims to create ANN modeling configurations and project the MSW collection rate based on the Chiang Mai City Center (CMCC) between 2023 and 2030. The objective of this project is to develop an artificial neural network (ANN) prediction model that forecasts the rate of MSW collection in a tourist city based on socioeconomic and demographic characteristics. This study was conducted in the Thai province of Chiang Mai (latitude: 18.7883°N, longitude: 98.9853°E) from 2023 to 2024.

MATERIALS AND METHODS

To effectively predict MSW collection, this study utilized data from 2015-2021 to synthesize supply and demand aspects of 18 tourism-related variable datasets using the knowledge discovery in database (KDD) approach. Additionally, ANN techniques were utilized to model the MSW gathering process. The study outlines the implementation of the MSW collection predictive model framework and the data mining and preparation steps carried out this study.

Model framework

Data mining and machine learning are utilized in this study to anticipate the daily municipal waste collection from CMCC. A predictive model is developed by comparing the effectiveness of various machine learning algorithms. This evaluation is intended to determine the daily MSW collection for Chiang Mai municipality, which serves as a collection area. This method considers the changes in waste generation patterns across different segments, which are impacted by demographic and socioeconomic features, along with external factors like events and policy variables, including the amount and percentage of locals and tourists. The methodology is illustrated in Fig. 1 as a framework.

Study area

The study focuses on the CMCC, which has a registered resident of about 228,443 persons and 90,664 residential dwellings in 2022, constituting about 12.8% of the total population of Chiang Mai province (Chiang Mai Municipality, 2022). CMCC encompasses densely constructed contemporary residences adorned with traditional Lanna artwork, expansive hotel compounds, retail centers, dining establishments, educational institutions, and universities, covering an area of approximately 115 square kilometers (km^2). Fig. 2 visually represents the CMCC study area. In 2020, CMCC comprised 90,664 residential dwellings, 58 retail and convenience outlets, 2,470 dining establishments, 439 hotels, 23 markets, 67 schools, six universities, 177 religious establishments, one international airport, governmental offices, and recreational facilities. In 2022, CMCC generated monthly MSW collection averages of 7,957 metric tonnes. The location of waste sources is shown in Fig. 2.

Data and predictor variables

This investigation utilized daily MSW collection and diversion data from the Chiang Mai municipality in 2015-2021 (Chiang Mai Municipality, 2022)—the Chiang Mai municipality for waste management, which includes curbside collection, depot collection, and recycling collection. On a daily basis, the collection

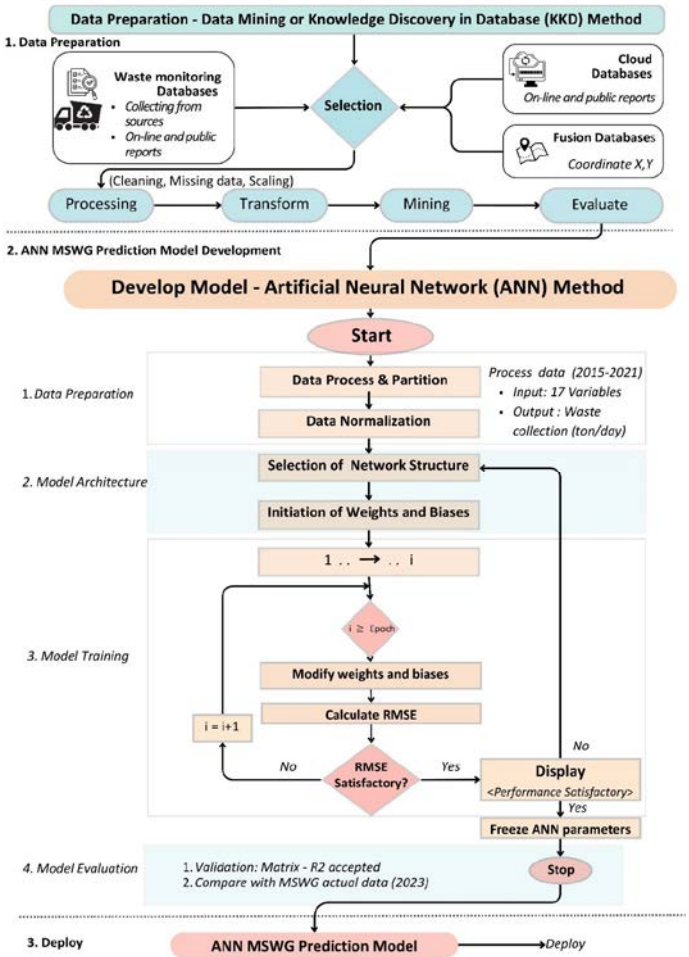

Fig. 1: ANNs prediction models of MSW collection framework

company manages the collection of common waste streams, which encompasses commercial and residential waste, while excluding hazardous and industrial waste in municipal waste collection. The amont of 810,077 metric tons of MSW, or one-quarter of the province's total garbage output, were collected from residential and institutional buildings in Chiang Mai's core region between 2015 and 2021. Chiang Mai province reported an average daily waste production of 0.98 kg per resident. The average daily waste production per resident in Chiang Mai province is 0.98 kg. At present, 35% of recyclable waste is recycled, with the remaining 65% is disposed of in landfills (Chiang Mai Governor's Office, 2022). Population characteristics are the key factors in determining the overall amount of MSW generation and have been utilized as a predictor in the long-term time series forecasting model (Abbasi and El Hanandeh, 2016; Kannangara *et al.*, 2018). The calculation of waste per icapita is determined through cross-sectional research that considers the population as a dependent variable when analyzing the amount of trash. This point assumes that the amount of waste created per person is independent of population size. The number of homes and household incomes in a municipality was utilized as the normalization factor in this study to compute garbage per household because data on the annual households served by waste collection services was available. The Chiang Mai Municipality compiles an annual report containing data on demographic

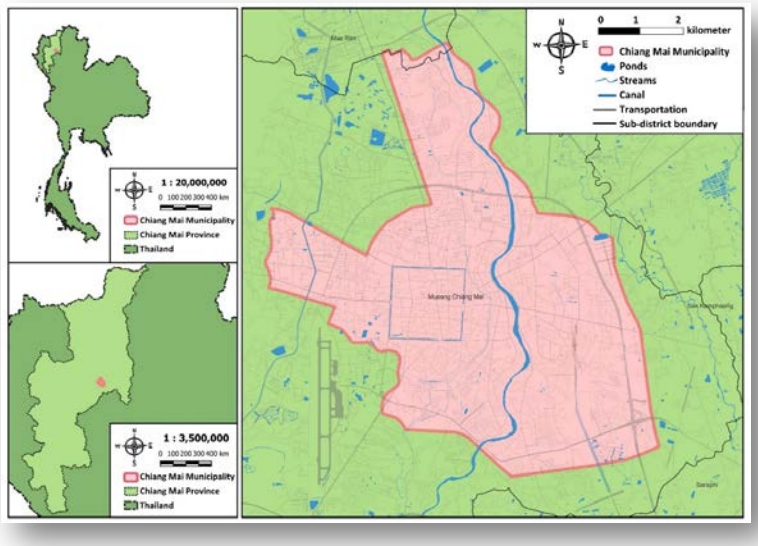

Fig. 2: Geographic location of the study of MSW collection in CMCC, Thailand

characteristics from various sources. It was assumed that other socioeconomic variables and the amount of garbage generated by each household are unaffected by the size of a municipality. The study opted to use Gross provincial product (GPP) instead of GDP to assess economic prosperity and standard of living, as it is more closely linked to the generation of waste. Waste generation correlates positively with variables like the purchasing power index, GDP, income level, and consumer spending. The primary criteria used in the study to select tourism variables were their presence at the provincial level and their relevance from a demand-supply standpoint. The Ministry of Tourism and Sports' annual nationwide records study was the most appropriate data source that satisfied these requirements. Socioeconomic factors, such as demand size, influence waste generation, such as the number of Thai and foreign visitors, the expenditure of tourists, and the period spent visiting. The supply side was integrated with the quantity of rooms available, check-in rooms, and hotel occupancy rate. The Thailand national holidays and festivals explained the seasonal SWG variations. The study involved transforming the data into an integer value using a rating scale. A score of 0 represents a regular working day, while a score of 1 represents a day with specific activities and festivals based on the Chiang Mai Municipality calendar, excluding holidays. According to the Thai calendar, a score of 2 indicates a weekend and public holidays. In the course of the study, collectors and operators observed that the operational status of schools can affect the amount of MSW collected. So, in Thai schools' semesters, the data has been transformed using a rating scale to identify integer values, where a score of 1 indicates a school day and a score of 0 indicates a school break day with specified public and private schools, according to the CMCC. For particulate matter with an aerodynamic diameter less than 2.5 microns (PM2.5) value and SARS-COVID-19 pandemic data affect the issues for tourism events. The data on PM2.5 value is an online report by The Pollution Control Department (PCD). The monitoring station located in the CMCC reports the daily average PM2.5 value. The CMCC's monitoring station provides daily average PM2.5 value reports. The SARS-COVID-19 pandemic data has been transformed into integer values using a rating system. A score of 0 represents a day without outbreaks, a score of 1 signifies a day during the outbreak period, and a score of 2 indicates a day when the government imposes lockdowns. The environmental practice policy announcements were chosen as a variable for the awareness and action of each sector in CMCC. The data has been converted into whole numbers through a rating system that correlates with the date of official government announcement Table 1. contains the predictor

variables and MSW assessed for modeling purposes in this study.

Knowledge discovery in databases (KDD)

KDD is a systematic procedure to extract meaningful insights, typically latent within extensive datasets or Big Data The data has been transformed into integer values using a rating score based on the date of government declaration. Table 1.. Data Mining is crucial for uncovering interesting data patterns, such as data characteristics, relationship patterns, data organization, grouping, and distribution. The KDD process consists of five essential steps: 1) Data Selection: identifying the data sources to be used and extracting the necessary data from the database for further preliminary examination; 2) Data Preprocessing or cleaning: ensuring data quality by eliminating inaccurate data. 3) Data Transformation: transforming selected data into a suitable format for analysis in accordance with the and models used in subsequent data mining. 4) Data Mining: using internal data mining techniques, which can be divided into predictive and descriptive Data Mining. 5) Interpretation and Evaluation: analyzing

Table 1: The predictor variables and MSW assessed for modeling

Sector	Variables		Unit	Sources
		Demand side		
Population	Total number of people registered in Chiang Mai municipality	(RR)	Capita	Chiang Mai Municipality, 2018, 2022
Population	Total number of registered households in Chiang Mai municipality	(NH)	Houses	
Population	Income per month in a household	(HI)	Baht/month	NSO, 2024
Economy	Gross regional and provincial Product	(GPP)	Million Baht	NSEDC, 2024
Economy	Average expenditure of Thai tourists per person	(ETT)	Baht/Person/Day	Ministry of tourism and Sports, 2015, 2016, 2017, 2018, 2019, 2020, 2021
Economy	Average expenditure of international tourists per person	(EFT)	Baht/Person/Day	
Tourists	Total number of Thai tourists visiting Chiang Mai province per month	(NTT)	Person	
Tourists	Total number of international tourists visiting Chiang Mai province per month	(NFV)	Person	
Tourists	Average of visitors stay overnight in Chiang Mai province per person	(TLS)	Day	
Supply Side				
Tourists	Number of guest arrivals at accommodation establishments	(NTA)	Person	
Economy	Number of occupied rooms for accommodation establishments	(NOR)	Rooms	
Economy	Percentage of occupied rooms per total sellable rooms	(OR)	Percentages (%)	
Events	Thai school's semester occurrences	(TSO)	Open/Break: 1/0	Tutorforhome, 2023
Events	Festival and events occurrences	(FEO)	Rating 0-3 0: Working Day 1: Festival, but not public holidays 2: Holidays/Weekend 3: Public Holidays	Thaiall, 2024
Events	Daily PM2.5 station 36T occurrences	(PMO)	µg/m3	PCD, 2024
Events	SARS-COVID-19 outbreak status Lock / shut Down	(CV19)	Rating 0-2 0: Normal Day 1: Outbreak 2: Lock down	Prachatai, 2022
Events	Environmental Practice Policy launch	(EPL)	Rating 0-5 0: No policy declaration 1-5: plus 1 for each the effective date of policy declaration	PCD, 2020 PCD, 2021
Output	Daily waste collected by municipality typically comprises household and commercial materials, excluding hazardous and industrial waste	(MW)	metric tonnes per day (T/d)	Chiang Mai Municipality, 2018, 2022

and interpreting the meaning and the outcomes acquired to ascertain their appropriateness or congruence with the intended objectives. Generally, the results are presented or visualized in easily understandable formats, such as graphs or images (GeeksforGeeks, 2023). The research investigates the correlation between dataset variables, emphasizing the coherence of data and their relationships. The value "r" is the Pearson Correlation coefficient, which shows the link between two variables. The correlation coefficient, which ranges from -1.0 to +1.0, represents the link between two variables. The two variables have a strong negative correlation, indicating they move in opposite directions if the value of r is near -1.0. On the other hand, if r is near +1.0, it indicates a significant positive correlation between the two variables, meaning they move in the same direction. A nonlinear relationship is present between the two variables when the correlation coefficient is 0. The correlation coefficient formula is determined by Eq. 1 (Bhandari, 2021):

$$r = \frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum(x_i - \bar{x})^2 \sum(y_i - \bar{y})^2}} \quad (1)$$

Where; r is the Correlation Coefficient, x_i is the value of variable x in dataset *i*, $\bar{x}$ is the average value of variable x, y_i is the value of variable y in dataset *i*, and $\bar{y}$ is the average value of variable y.

Artificial neural network (ANN)

Within a mathematical framework, an artificial neural network (ANN) is composed of interconnected nodes that function as or basic processing units. ANN's architecture usually consists of three layers. Studies have shown that artificial neural networks with a single hidden layer can effectively approximate complex nonlinear functions (Azadi and Karimi-Jashni, 2016). In addition to acting as a buffer layer, the input layer supplies the network with the input data. The total count of independent variables or input data points matches number of nodes in this layer. The weight assigned to each connection between a node and the hidden layer nodes, as well as other layers, signifies the intensity of their relationship. The activation function of the hidden layer utilizes the cumulative weights to determine the relationship between the input and output values (Xu *et al.*, 2021). The y_j is the output of any node j, using Eq. 2 (Gajawada, 2019), and Fig. 3 shows the mathematical function ANN diagram.

$$y_j = f\left(\sum_{i=1}^{m} W_{ji} X_i + b_j\right) \quad (2)$$

Where, X_i represents the output of the ith connecting node in the previous layer,

W_{ji} is the weight between the ith node in the previous layer and the jth node, and b_j is the node threshold.

Several methods have been proposed to determine the number of neurons in a single hidden layer network: "2n + 1", "2n", "n", and "n/2", where "n" is the number of independent variables. None of these standards, nevertheless, apply to everyone. By employing a confidence interval and adhering to the recommendations, the number spanned from 1 to 15. The identification of the optimal number of hidden neurons was then established through an assessment of the prediction error findings. A confidence interval was utilized to account for the range of numbers, which spanned from 1 to 15, in line with recommended practices. The most suitable number of hidden neurons was subsequently identified through an analysis of prediction error data (Azadi and Karimi-Jashni, 2016; Mijwil, 2021). This investigation made use of one of RapidMiner's hidden layer functions. The best activation function in the hidden layer for forecasting with the validation procedure was then determined by comparing the prediction errors of each state.

Models training and validation

During the modeling phase, a function (model) was identified by utilizing the prepared datasets to establish a connection between socioeconomic variables and daily quantitative MSW characteristics for 2015 to 2021. The effectiveness of machine learning algorithm-generated models may be compromised if they are overfitted and applied to new datasets. Therefore, it is imperative to evaluate the model using never-before-seen data. In order to accomplish this, the dataset was split into a training set and a testing set. The training set was utilized for model development, while the testing set was employed to identify over-fitting. Previous studies often used training to test 80:20 partition ratios or varied training to test ratios (Kannangara *et al.*, 2018). For every ratio, 100 random partitions were made,

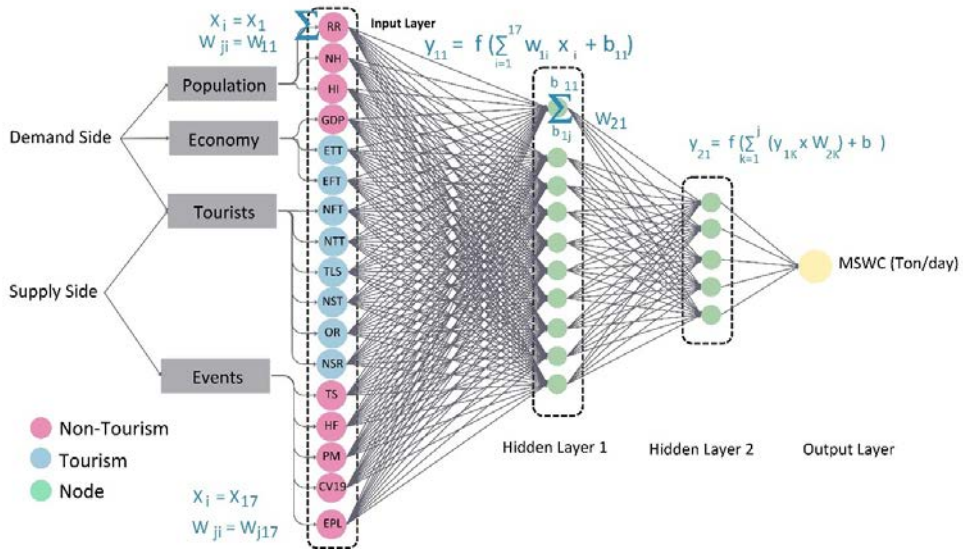

Fig. 3: ANNs diagram for MSW models

and each dataset was used to train a model. The selection of the ratio was determined by the lowest average model error. The primary performance variable, prediction accuracy, can be examined using training data. The difference between the target and anticipated values is the forecasting error, which is a gauge of accuracy. In order to assess how well the models performed in this investigation, four accuracy metrics were established. Using Eqs. 3, 4 and 5. The root mean square error (RMSE), mean absolute percentage error (MAPE), and mean squared error (MSE) was used to evaluate the predictive validation of the model (Oppermann, 2022):

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

Where, MSE is a mean squared error, n is a number of data points, y is the observed value, and $\hat{y_i}$ is the predicted value.

$$\mathrm{MAPE} = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right| \quad (4)$$

Where, MAPE is the mean absolute percentage error, *n* is the number of times the summation iteration happens, A_t is the actual value, and F_t is the forecast value.

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_i - \hat{y_i}\right)^2} \quad (5)$$

Where, RMSE is root mean square error, n is number of data points, y_i is observed values, and $\hat{y_i}$ is predicted values.

A model that shows a falling Mean Squared Error (MSE) is considered very accurate. Similarly, good model performance is indicated by a Root Mean Squared Error (RMSE) close to zero, and performance gets even better as the Mean Absolute Percentage Error (MAPE) gets closer to zero. Employing multiple accuracy metrics concurrently enhances the precision of the study and strengthens the problem-solving methodology. No accuracy metric is appropriate in every circumstance, and each has unique advantages and disadvantages (Azadi and Karimi-Jashni, 2016).

RESULTS AND DISCUSSION

A study was conducted to determine the Correlation Coefficient, r, for the relationship between 18 variables, including the consistency of the dataset. The result shows that the r value has a negative and positive correlation; the r values are diverse relationships between -0.87 and +0.99. However, The correlation between daily MSW collection rates and the 17 variables, with an r value ranging from -0.12 to 0.29, suggests that the dataset follows a non-linear regression model. This r value can be visualized in Fig. 4**.** A study was conducted to determine the most effective analytics method, especially ANN structure, for forecasting the mean MSW collection rate. Various

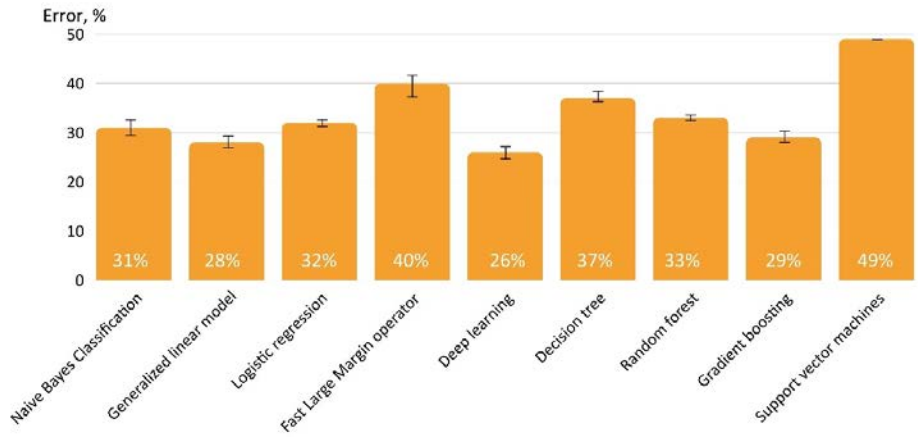

Fig. 4: The overview of the modeling method and classification error

algorithms were utilized to analyze nine different methods. The input datasets are ready to be used for modeling. However, the deep learning methods show a classification error of 26%, which is lower than the others. The results are shown in Table 2. The 18-variable datasets used in this research illustrate the model's effectiveness and capability as an ANN.

Variation of training and testing models

A study has determined the best artificial neural network (ANN) setup for predicting the average rate of MSW collection. Additionally, the study explored ANN structures that integrate two transfer functions, diverse training methods, and various node and hidden layer setups. Three accuracy metrics—the correlation coefficient, Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE)—were used to select the finest networks. The results of training and testing in the transfer function are shown in Table 3. Table 4 shows an optimal ANN network and a transfer function on eight nodes using a dataset with 17 variables. Moreover, the study investigated artificial neural network architectures that combine two different transfer functions, a range of training techniques, and various configurations of nodes and hidden layers.

The ANN architecture is established through the training and testing of models up to the eighth iteration, which takes place at the beginning of the training phase. As the network overfits the data, mistakes in the validation dataset grow while those in the training dataset decrease. The training will be terminated at the point of the lowest validation if the justification error occurs in two consecutive epochs. In the trial shown in Table 3 and Fig. 4, the performance vector is achieved by training and testing ANN models. Among the trials conducted, Trial-6, with eight variables input across two layers (with 10 and 5 nodes, respectively), exhibits the lowest prediction error, indicated by an RMSE of 16.478 +/- 0.000 T/d and MAE of 320.78 +/- 22.08, showing improvement compared to previous trials. The correlation coefficient of 0.674 indicates a moderate relationship and is not statistically significant. However, Trial-8, with 17 variables input across two layers (with 8 and 4 nodes, respectively), exhibits a slightly higher prediction error compared to Trial-6, with an RMSE of 21.891 +/- 0.000 T/d and MAE of 461.95 +/- 706.680. The correlation coefficient of 0.687 indicates a moderate relationship and no statistically significant difference. Previous studies have frequently shown that the number of nodes is usually divided into less than the input variables, with around 50% of nodes in the initial layer being used (Xu *et al.*, 2021). Furthermore, the correlation coefficients of the 17 variables with daily MSW collection range closely from -0.12 to 0.29. Hence, Trial-8 was picked as the model to predict outcomes in upcoming forecasting trials. The significant variables are shown in the Sigmoid value on the hidden layer of each variable in Fig 5.

The significant variables are shown as Sigmoid values on hidden layers,n layers of each variable reliable, and the table is shown in Tables 4 and 5.

The ANN performance models for MSW collection rate predicting

Ensuring the normal distribution of the dependent

Table 2: The correlation coefficient of the dataset variable

Dataset variable	MW	RR	NH	IH	GPP	NTT	NFT	TLS	ETT	EFT	NOR	OR	NTA	FEO	TSO	CV19	PMO	EPL
MW	1																	
RR	0.00	1																
NH	0.07	-0.85	1															
IH	0.06	-0.87	0.91	1														
GPP	0.18	-0.53	0.64	0.73	1													
NTT	0.21	0.37	-0.29	-0.29	0.10	1												
NFT	0.10	0.64	-0.60	-0.61	-0.04	0.57	1											
TLS	0.20	0.26	-0.12	-0.11	0.05	0.02	0.15	1										
ETT	0.23	0.15	0.03	0.05	0.42	0.73	0.40	-0.03	1									
EFT	0.29	0.33	-0.13	-0.05	0.45	0.60	0.61	0.07	0.76	1								
NOR	0.23	-0.53	0.77	0.73	0.70	-0.03	-0.30	0.08	0.33	0.25	1							
OR	0.19	0.61	-0.54	-0.54	0.01	0.91	0.82	0.15	0.63	0.65	-0.23	1						
NTA	0.19	0.55	-0.47	-0.46	0.08	0.93	0.80	0.08	0.69	0.70	-0.15	0.99	1					
FEO	-0.02	-0.03	0.04	0.02	0.03	0.02	-0.03	0.01	0.00	-0.04	0.00	0.00	0.00	1				
TSO	0.22	-0.08	0.02	0.00	0.00	0.12	0.05	-0.02	0.08	0.00	0.00	0.12	0.10	-0.13	1			
CV19	-0.12	-0.68	0.65	0.67	0.10	-0.63	-0.83	-0.08	-0.40	-0.60	0.42	-0.85	-0.81	0.01	-0.02	1		
PMO	-0.08	0.14	-0.11	-0.01	0.02	0.10	0.09	-0.09	0.21	0.27	0.09	0.07	0.12	-0.01	-0.47	-0.03	1	
EPL	0.06	-0.83	0.88	0.87	0.72	-0.27	-0.52	-0.19	0.07	-0.06	0.77	-0.49	-0.41	0.03	0.01	0.59	-0.01	1

Table 3: The performance vector training and testing of ANN models

Trial	ANNs structure			Performance vector			
	ID	Node		RMSE (T/d)	MAE (T/d)	Prediction average (T/d)	Correlation coefficient
		L- 1-	L- 2				
1	17	10	4	26.361	694.901 +/- 2,806.120	315.986 +/- 35.162	0.668
2	17	10	4	26.616	708.394 +/- 2,866.883	315.986 +/- 35.162	0.676
3	8	4	2	30.296	917.846 +/- 2,705.129	315.986 +/- 35.162	0.533
4	8	3	2	28.074	788.146 +/- 2,748.221	315.986 +/- 35.162	0.614
5	17	8	4	26.770	716.608 +/- 2,879.917	315.986 +/- 35.162	0.661
6	8	10	5	16.478	320.779 +/- 22.080	315.986 +/- 35.16	0.674
7	17	8	4	24.436	597.126 +/- 874.052	316.484 +/- 32.238	0.653
8	17	8	4	*21.891*	*4*61.953 +/- 706.680	315.986 +/- 35.162	0.687

Table 4: Sigmoid value on hidden layer 1

Hidden 1	Node 1	Node 2	Node 3	Node 4	Node 5	Node 6	Node 7	Node 8
RR:	-0.05	0.80	-0.68	-0.13	0.94	-1.43	-1.10	0.34
NH:	0.34	0.28	1.25	0.24	0.23	0.60	0.72	0.40
IH:	-0.27	-0.46	0.20	-0.36	-0.77	0.14	0.33	-0.35
GPP:	0.10	-0.04	0.55	0.07	-0.64	0.92	0.03	0.12
NTT:	-0.56	-0.10	-0.59	-0.79	-0.59	1.22	-1.06	-0.16
NFT:	0.21	0.33	1.06	0.44	-0.01	-1.34	0.29	0.43
TLS:	0.77	0.76	0.60	1.18	0.82	-0.35	0.24	0.64
ETT:	-0.39	0.11	-2.34	-0.59	-0.40	2.90	-1.65	-0.21
EFT:	0.20	0.66	0.05	0.21	0.19	-0.28	-0.33	0.55
NOR:	0.62	0.82	0.55	1.03	0.61	-0.58	0.10	0.78
OR:	-0.37	-0.10	-0.14	-0.49	-0.45	1.27	-0.98	-0.07
NTA:	-0.24	0.07	0.09	-0.46	-0.41	1.01	-0.62	0.07
FEO:	-0.16	-0.19	0.11	-0.18	-0.17	0.19	0.01	-0.18
TSO:	-0.18	0.42	0.39	0.33	-0.15	-0.03	0.94	0.00
CV19:	0.64	0.14	-0.09	1.26	0.19	-0.43	0.64	0.31
PMO:	0.01	-0.08	-0.32	-0.01	-0.52	-0.32	0.31	-0.21
EPL:	-0.33	0.15	0.39	-0.99	-0.94	-2.16	-0.56	0.13
Bias:	*-0.76*	*-0.84*	*-1.14*	*-1.14*	*-0.53*	*1.96*	*-0.94*	*-0.87*

variable is a necessary requirement. The mean MSW collection rate serves as the dependent variable. The Kolmogorov-Smirnov test can be used to assess whether this variable has a normal distribution. Thus, this test was run, and the outcomes are displayed in Table 6. With 2,458 records, the table has an average of 318.5 and a standard deviation of 27.3. The data also indicate a statistically insignificant (two-tailed) value of 0.802. A p-value less than 0.05 rejects the normalcy hypothesis, while a p-value greater than 0.05 supports the normality hypothesis. When considering a significance threshold of 0.05, the p-value of 0.802, which is above 0.05, does not raise concerns about the normal mean distribution of the MSW collection rate. A scatter plot is an efficient method for displaying the relationship and level of correlation between two sets of data. A straight line in a scatter plot indicates a high correlation between the two variables. A strong correlation suggests that the connection is meaningful if the slope of the data is equal to one. The scatter plot in Fig. 7a showcases the observed and predicted values of the best ANN model when applied to the complete data set. There is a strong correlation between the mean MSW collection rate's observed and projected values. The data presented in this graph was analyzed using a linear regression model. The identity line (1:1) was compared to the linear regression model, comparing observed and anticipated values, and the difference between the fitted and 1:1 lines was validated at a 1% significance level. The findings showed an insignificant slope and intercept difference at confidence levels of 1.0 and 0.0 of the regression line. The outcomes validate the ANN's exceptional predictive capacity in predicting the average MSW collection rate for CMCC.

The ANNs MSW collection rate models performed

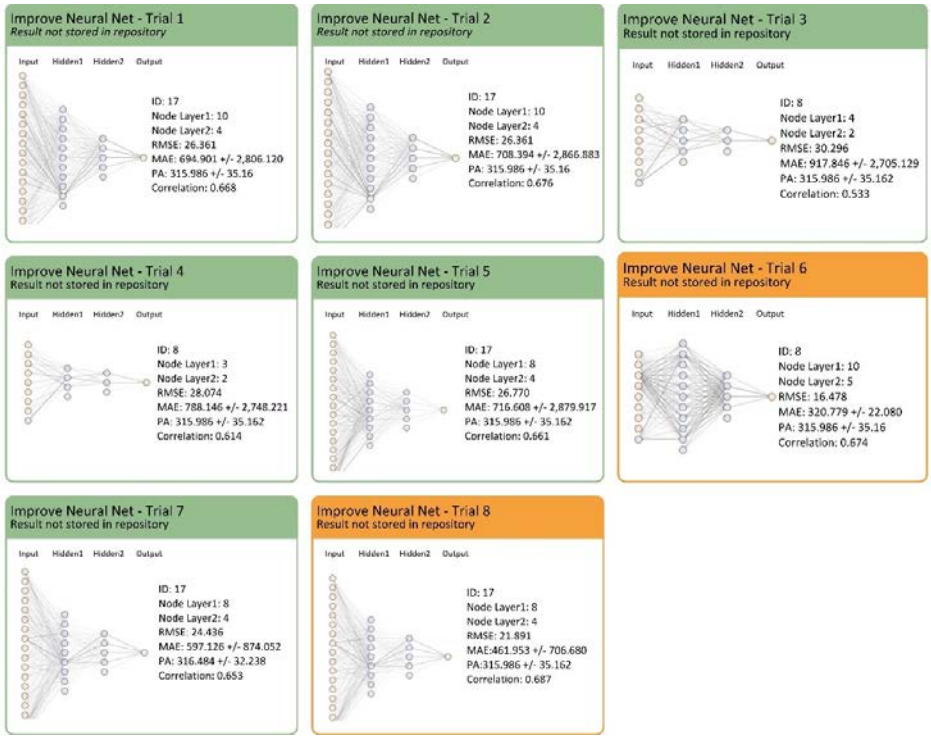

Fig. 5: ANNs training and testing models structures

Table 5: Sigmoid value on hidden layer 2

Hidden 2	Node 1	Node 2	Node 3	Node 4
Node 1	-0.09	-0.11	-0.15	-0.15
Node 2	-0.36	-0.37	-0.35	-0.35
Node 3	-0.68	-0.64	-0.85	-0.78
Node 4	-0.54	-0.58	-0.45	-0.49
Node 5	-0.37	-0.35	-0.28	-0.31
Node 6	-2.18	-2.32	-1.67	-1.94
Node7	-0.63	-0.57	-0.80	-0.78
Node 8	-0.27	-0.28	-0.18	-0.19
Bias:	0.30	0.35	0.05	0.21

effectively during the training phase, achieving an RMSE value of 21.891 +/- 0.000; significant disparities were seen among the models during the testing phase. Fig. 7b illustrates the predictive accuracy of ANNs MSW collection rate models. The sigmoid function is particularly effective in forecasting the monthly average quantities of waste generated..

Forecasting MSW collection *rate by ANNs models*

From Trial-6, it is crucial to note that several variables, such as the RR, ETT, OR, NTA, TSO, CV19, PMO, and EPL, impact the ANN MSW collection rate models. Thus, the study chose eight variables out of 17 to develop a model predicting the MSW collection rate for 2023 and 2030. The data used for forecasting in 2023 can be retrieved from various sources during the year. The six factors are as follows: RR reported population numbers range from 137,858 to 138,244 capital (Chiang Mai Municipality, 2023, 2024). ETT ranges from 5,124 to 11,860 baht per tourist per trip. OR ranges from 75% to 91%. NTA ranges from 889,897 to 1,419,658 people per month (Ministry of Tourism and Sports, 2023). The annual average of PM2.5 levels ranges from 4.9 to 236 ppm (PCD, 2024). CV19 is determined to be 0 due to the end of the lockdown period. EPL is determined **five** as there have yet to be

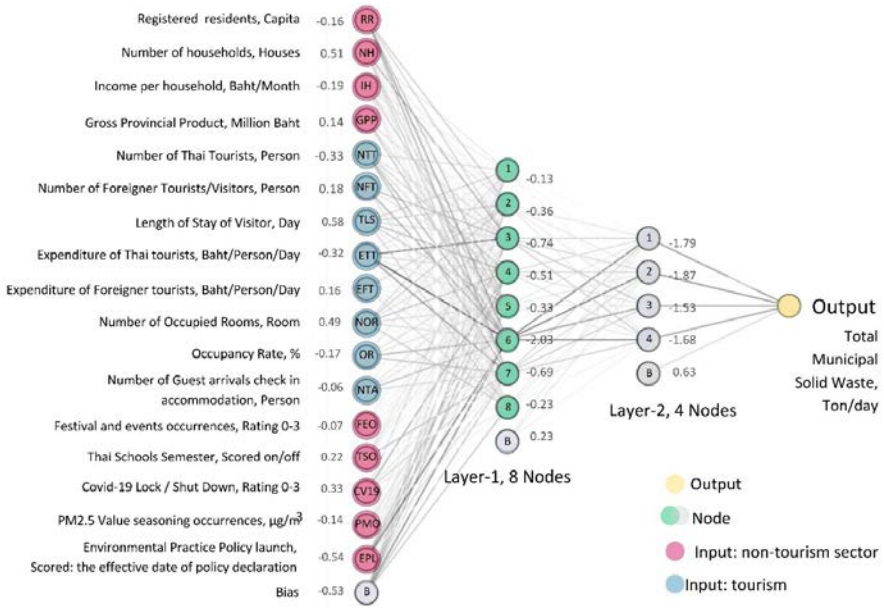

Fig. 6: The ANNs structure training and testing models

Table 6: The input forecasting variables and results for 2023 and 2030

Input predicting variables	RR	ETT	OR	NTA	CV19	PMO	MSW collection Prediction
	Capita	Baht/Person	(%)	Person	Score 0-1-2	µg/m3	T/d
2023	138,051	8,492.0	83.00	1,154,778	0	33.0	348.24
RR	138,051	3,211.6	56.78	550701	1	22	338.36
ETT	122627	8,492.0	56.78	550701	1	22	348.91
OR	122627	3,211.6	83.00	550,701	1	22	276.56
NTA	122627	3,211.6	56.78	1,154,778	1	22	351.75
CV19	122627	3,211.6	56.78	550,701	0	22	354.55
PMO	122627	3,211.6	56.78	550,701	1	33.0	354.55
2030	140,757	25,359	94	1,712,535	0	33.0	360.76
RR (↑0.28%/y)	140,757	3,211.6	56.78	550701	1	22	388.69
ETT (↑6.9% /y)	122,627	25,358.8	56.78	550701	1	22	274.77
OR (↑1.9% /y)	122,627	3,211.6	94.00	550,701	1	22	342.47
NTA (↑6.9% /y)	122,627	3,211.6	56.78	1,712,535	1	22	360.15
CV19	122,627	3,211.6	56.78	550,701	0	22	354.55
PMO	122,627	3,211.6	56.78	550,701	1	33.0	354.55

any recent announcements of new laws.

To forecast the rate of change for variables in the 2030 prediction, this study derived estimates from the average rate of change over the past eight years, from 2015 to 2023. These estimates served as a basis for projecting input data for the 2030 forecast. RR demonstrated an annual increase rate of 0.28% per year. While the ETT fluctuated annually, the average increase was 6.9% yearly. Similarly, the NTA exhibited a comparable trend to ETT, resulting in the same average value. The OR experienced fluctuations annually, but the OR average increase amounted to 1.9% per year. The forecasted outcomes demonstrate a strong connection between the six variables in relation to the MSW collection rate trend. However, the ETT has an adverse effect, as indicated in Fig. 6. The ANNs model predicted an MSW collection rate of 348.2 metric tonnes per day for 2023, surpassing

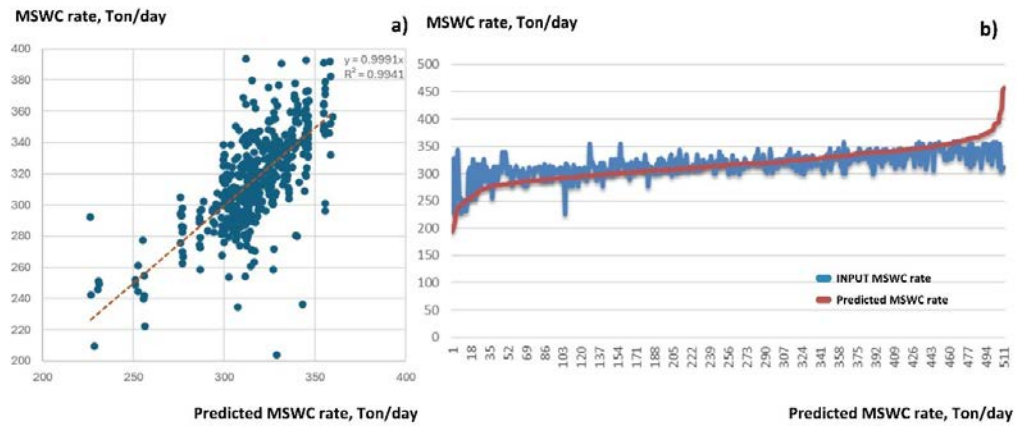

Fig. 7: Scatter plot and comparison of observed inputs versus predicted MSW collection rate

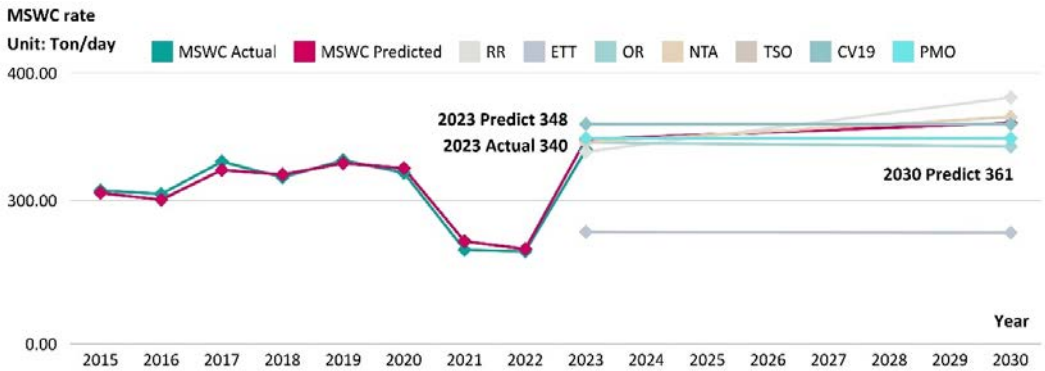

Fig. 8: The prediction of MSW collection rate in 2023 and 2030.

the actual MSW collection rate of 340 metric tonnes per day by 2%. Additionally, the model predicts a rate of 360 metric tonnes per day for 2030. Table 6 displays the input forecasting variables along with the predicted results for the ANNs MSW collection rate model in 2023 and 2030. Fig. 8 shows the prediction of the MSW collection rate in 2023 and 2030.

Limitation

In this study, it is important to consider multiple limitations when creating prediction models using ANNs. ANNs are frequently referred to as “black box” models since it can be challenging to understand how they produce a given result. Deciphering the decision-making mechanisms of intricate models like ANNs can be quite challenging. ANNs have been shown in numerous studies to be susceptible to overfitting, a phenomenon in which the model learns to recall the training set rather than identifying underlying patterns. The performance on data that has not been previously seen may be negatively impacted. Despite a small 2% variance between the predicted and actual outcomes, the error in prediction for this research is deemed to be within an acceptable range. Furthermore, a lot of processing power is needed to conduct trials to create models with deep neural networks (ANNs) with numerous layers and parameters. Achieving peak performance in artificial neural networks (ANNs) necessitates precise adjustment of various hyperparameters such as layer count, node quantity per layer, and learning rate. Selecting the ideal hyperparameters can be difficult and time-consuming. Adversarial attacks can cause noticeable changes in the output of ANNs, from tiny, unnoticeable perturbations to the input data. There are security concerns, particularly in areas like image

recognition and autonomous driving. Furthermore, scientists always look for new ways to boost ANNs' efficiency, interpretability, and resilience.

CONCLUSION

The objective of this study is to develop a predictive model for MSW collection, specifically targeting CMCC. The research combines a socio-spatial model of daily MSW generation with assessments of the city's 115 km2 area, utilizing an ANN method for predictive modeling. The ANN MSW collection rate model can forecast total daily MSW collection with an out-of-sample RMSE value of the daily input data for training and testing ANNs models from 7 years of records, 2015-2021 with 46,023 input data, with separated training 80% and testing 20%, and design two layers with 8 and 4 nodes were success model development. Of the 18 variables, eight had the highest feature relevance weight value, including RR, ETT, OR, NTA, TSO, CV19, PMO, and EPL. The construction prediction model shows good accuracy levels after undergoing two validation processes. The model's performance determines that RMSE is 16.5 T/d, correlation is 0.67, and R2 is 0.99. The prediction of the MSW collection rate for 2023 is 348 T/d, with an anticipated margin of error of 2% from the actual amount of 340 T/d. In 2030, the model predicted that waste generated 361 metric tonnes daily. The study showcased the construction process by employing rate models with non-linear regression variables, demonstrating the use of vast amounts of data not previously utilized in similar studies, especially secondary data for predictive purposes. This approach helps save costs in data collection and surveying. The ANNs MSW collection rate models contribute to proactive measures to minimize environmental impact. Understanding future trends in waste generation enables authorities to develop plans for reducing waste, implementing recycling programs, and promoting sustainable waste management practices. Utilizing variables associated with tourism and urbanization yields greater advantages than depending solely on demographic variables. With accurate waste generation forecasts, tourist municipalities can efficiently plan resource allocation, leading to optimized waste management operations and reduced unnecessary expenses, such as fuel costs, labor, and maintenance fees. It involves planning adequate waste collection routes, staffing levels, and equipment utilization. Urban planning and policymaking can benefit greatly from reliable waste prediction models, as they offer valuable insights. Authorities can utilize this information to devise effective waste management policies, infrastructure projects, and long-term sustainability strategies. Expanding on this study, future initiatives can leverage forecasted values to construct waste management models. This can be accomplished by studying waste components in diverse urban sectors to determine waste categories for additional analysis and the formulation of future management models.

AUTHOR CONTRIBUTIONS

D. Rinchumphu, the corresponding author, has supervised the work, concept formulation, and manuscript edition. T. Kridakorn Na Ayutthaya has contributed to data evaluation and analysis, prepared all the maps and figures, interpreted the results, and prepared the manuscript. N. Jakrawatana has supervised the model results and manuscript preparation. V. Owatsakul has provided research data from Chiang Mai municipality.

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CONFLICT OF INTEREST

The authors declare that there is no conflict of interests regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancy have been completely observed by the authors.

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ABBREVIATIONS

%	Percent
µg/m3	Micrograms per cubic meter air
AI	Artificial intelligence -
ANNs	Artificial neural networks -
CMCC	Chiang Mai City Center
COVID-19	Coronavirus disease 2019 caused by SARS-CoV-2
CV19	SARS-COVID-19 lock up and shut down by
DL	Deep Learning
EFT	Expenditure of foreigner tourists
EPL	Environmental Practice Policy launch
Eq.	Equation
ETT	Expenditure of Thai tourists
FEO	Festival and events occurrences
FFNN	Feed-forward neural network
Fig.	Figure
GDP	Gross domestic product
GPP	Gross provincial product
HI	Income per household
KDD	Knowledge discovery in database
kg	Kilograms
km.	Kilometers
km^2	Square kilometers
MAE	Mean absolute error
MAPE	Mean absolute percentage error
ML	Machine learning
MLR	Multiple linear regression
MSW	Municipal solid waste
NESDC	Office of the National Economic and Social Development Council
NFV	Number of foreigner tourists/visitors
NH	Number of households
NSO	National Statistical Office of Thailand
NOR	Number of occupied rooms
NTA	Number of guest arrivals
NTT	Number of Thai Tourists
OR	Occupancy rate
PCA	Principal component analysis
PCD	Pollution Control Department
PM2.5	Particulate matter with an aerodynamic diameter less than 2.5 microns
PMO	PM2.5 seasoning occurrences
RMSE	Root mean square error
RR	Registered residents
SDGs	Sustainable development goals
SW	Solid waste
SWG	Solid waste generation
T/d	metric tonnes per day
TLS	Length of stay of visitor
TMSW	Total municipal solid waste
TSO	Thai Schools Semester
UNEP	United Nations Environment Programme

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