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Construction Waste Modeling for the Republic of Serbia

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The management of Construction Waste (CW) presents a significant challenge in sustainable development efforts. This study employs data modeling techniques to predict the annual quantities of various types of construction waste, encompassing total waste, metal waste, plastic waste, wood waste, mineral waste, and soil/concrete waste (CW1–CW8, respectively). The study has mainly focused on reusable construction waste. For this purpose, 7 models were developed for each type of construction waste – 5 polynomials (from the first to the fifth degree), Artificial Neural Network (ANN) and Support Vector Machine (SVM) models. The ANN models were found to be the most effective for all types of CW compared to the other models developed. The ANN models developed for CW1, CW6 and CW7 had a high R^2 value (> 0.85), indicating their potential for predicting the amount of these types of CW in the future. The ANN models developed for the remaining types of CW had weaker performance ($R^2 < 0.60$), but their performance could be improved in the future investigations with an increase in the amount of data on CW generation. This research underscores the importance of employing advanced data modeling techniques in addressing the challenges of construction waste management. By providing accurate predictions of CW generation, stakeholders can better strategize waste reduction, recycling, and disposal efforts, thereby contributing to the sustainable development goals of minimizing environmental impact and promoting resource efficiency in the construction sector.

Keywords: Artificial neural network, Construction waste prediction, Data modeling techniques, Support vector machine, Sustainable construction

Introduction

The Republic of Serbia boasts a robust economy and industry abundant in reusable resources, playing a pivotal role in fostering a circular economy.[1] As part of Serbia's integration into the EU, numerous laws have been enacted, most of which are quite applicable. However, there are instances where these laws do not align with Serbia's needs and potential, particularly evident in the construction sector. This industry generates substantial waste materials that hold the potential for high-quality reuse, yet current regulations don't fully capitalize on this opportunity. Construction Waste (CW) arises from various stages like production, demolition, and reconstruction, encompassing a range of materials. These materials span from earthworks such as soil, sand, gravel, and stone to materials from civil engineering like cement and asphalt, along with products from high-rise construction like concrete, brick, and gypsum. Additionally, mixed construction waste includes wood, plastic, paper, cardboard, metals, cables, paints, varnishes, and rubble.[2]

In the Republic of Serbia, the demolition of buildings and disposal of waste is carried out unplanned without prior analysis of the material from which the building was built, examination of the influence of that material on the environment, and a disposal plan.[1] The preliminary analysis of the material determines the method of demolition and the procedure, as well as the type and treatment of the resulting waste through on-site filling, removal to temporary storage or recycling, or final disposal. The primary aim of managing construction waste revolves around creating a sustainable system that oversees and tracks the volume, variety, and makeup of this waste. It focuses on preventing its generation, minimizing the amount sent for disposal, and effectively segregating and disposing of all forms of construction waste, particularly those containing hazardous substances.[2] When we talk about demolition, construction waste from demolition, construction,

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renovation, adaptation and reconstruction, what is defined in the Republic of Serbia is through the Law on Spatial Planning and Construction[3], the Law on Waste Management[4], which is an integral part of the Waste Catalog[5] and Rulebook on Categories and examination - classification of waste[6] and the Law on Environmental Protection.[7] The legislation of the Republic of Serbia is written according to the patterns of the European Union, but not to the end and to the extent that waste management and the implementation of the legislation would be applicable, that is, it is necessary to pass by-laws in the form of regulations and rulebooks. Regulations and enhanced management practices are pivotal and essential factors in advancing the handling of this particular waste type.[8]

Previous researches in the world on construction waste and management systems for this waste flow are based on mathematical and theoretical models.[9] Different level of development of countries, mentality, method of construction, climatic conditions, materials used, awareness of environmental protection are factors that certainly affect the level of generation and management of construction waste.[10–15] The mentioned factors reflect the level of development of waste management in certain countries, which can be seen from the works commented on here.

The achievement in construction waste management in Costa Rica (Central America) is such that the total annual amounts, excluding the types of waste, are generated, and the causes of waste generation are design, construction, material management, residues and other activities.[10] Research on the topic of construction waste management in Brazil, through the tools that waste can estimate.[16] In USA, an economic model of hybrid life cycle assessment related to the supply chain was developed.[17] Construction waste management in Canada through source reduction, a dynamic approach based on building information modeling, is the subject of the research.[11] The exploration of construction waste management in China (2018) involved developing both an SD (system dynamics) model and an ABM (agent-based modeling) approach.[18] The dynamic model for construction waste management[19] in China, presented in 2017, specifically focused on analyzing waste reduction during the design and construction phases. Despite numerous regulations and guidelines, construction waste management in India is unsatisfactory. The project is reflected in a new approach and research on waste management based on four methods: waste quantification, Influence Factors (IFs) by factor analysis, IF ranking according to the importance index, and confirmation of conclusions based on contractor interviews.[18] A dynamic system based on Information Modeling Of Buildings (BIMs) from 2020, was developed in Iran[19], and related to waste analysis using BIM. The reduction of construction waste is dealt with by a group of authors from a university in Australia[20], integrating Modular Coordination (MC) and parametric design, which is an insufficiently researched area, and the practical application itself is in the domain of rhetoric. The model developed at the Moscow State University of Civil Engineering consists of two subsystems.[21] The first includes the collection, separation and transport of waste, and the second a subsystem for recycling construction waste. Spain's construction sector undertook a Life Cycle Assessment (LCA) study to evaluate waste management options, catalyzing governmental regulations.[12] The model that even initiated a government regulation in Spain in 2009 is the work of a group of authors.[22] Waste quantification is very necessary for contractors to be able to plan the project to the end, including a waste management plan with a proposal for its disposal. The topic of waste disposal with the application of the circular economy is covered in a study where composite systems for external thermal insulation are types of treated waste, Germany (2020).[13] The construction waste management through a quantified eco-cost model based on an empirical study in construction was performed by University of Liverpool, UK.[23] The model, which was developed in Sweden in 2005, describes the methodology of the real costs of the generated construction waste with the aim of environmental management.[24] The research conducted in Egypt refers to the reduction of construction waste through the procurement of materials, that is, through the link between the project and execution, and through European practices.[25] In Ghana, stakeholders' roles in construction waste management are under scrutiny, elucidating pathways for enhanced collaboration.[14] Similarly, Qatar assesses its construction waste scenario, delineating actionable measures.[26] Oman explores sustainable construction practices, offering insights for project stakeholders.[27] Research on construction waste was conducted based on a survey of contractors, that is professional construction personnel in Nigeria.[15] Croatia explores the application of waste glass and recycled materials in concrete production, indicative of a broader sustainability agenda.[28,29] Notably, the Republic of Srpska faces challenges in documenting construction waste types, quantities, origins, and disposal methodologies, necessitating comprehensive waste management strategies.[30]

Surrounding countries have three publications, the Republic of Bosnia and Herzegovina has two, and the others have none. Construction waste is an unexplored area in the Republic of Serbia, and there are no published studies so far.

Upon examining research worldwide, significant variations in waste treatment practices become apparent. Estimating the quantities that will occur in future a year using a mathematical model has yet to be done. The primary objective of this study was to explore the feasibility of mathematically modeling the volume of annual construction waste generated in the Republic of Serbia. To achieve this, various models, including polynomial models, artificial neural networks, and support vector machines, were constructed using data spanning nine years. These models were tailored not only for the total construction waste but also for specific categories within this waste stream. To assess their effectiveness, the models were rigorously evaluated and compared using the statistical test "goodness of fit." The importance lies in creating a model that accurately predicts construction waste amounts, enabling forecasts for future periods based on historical data.

Materials and Methods

Data

The data used in this paper were taken from the Statistical Office of the Republic of Serbia. Data on the annual amount of Construction Waste (CW) for the period from 2012 to 2020 were used. In addition to the total amount of construction waste, data on individual categories of construction waste for the same period were also used. The types of construction waste and their corresponding labels used in this paper were depicted in Table 1. The study has focused mainly on reusable construction waste.

Table 1 — Type of construction waste

Label	Construction waste types
CW1	Total waste
CW2	Waste iron
CW3	Iron free metal waste
CW4	Iron mixed metal waste
CW5	Plastic waste
CW6	Wood waste
CW7	Mineral waste
CW8	Soil/concrete waste

Table 2 — Mathematical models

Label	Model
M1	$y = a + b \cdot G$
M2	$y = a + b \cdot G + c \cdot G^2$
M3	$y = a + b \cdot G + c \cdot G^2 + d \cdot G^3$
M4	$y = a + b \cdot G + c \cdot G^2 + d \cdot G^3 + e \cdot G^4$
M5	$y = a + b \cdot G + c \cdot G^2 + d \cdot G^3 + e \cdot G^4 + f \cdot G^5$
ANN	Artificial Neural Network
SVM	Support Vector Machine

y – output variable
G – input variable (year)
a, b, c, d, e, f – regression parameters of equations

Mathematical Modeling

For the purpose of mathematical modeling of data on construction waste, polynomial equations from the first to the fifth degree (M1–M5, respectively), Artificial Neural Network (ANN) and Support Vector Machine (SVM), were used. All developed models are summarizing in Table 2. Year (G) was the input (independent) variable and the amount of construction waste (CW1–CW8) was the output (dependent) variable for all models. Development of the models was done by the software package TIBCO STATISTICA 13.3.0 (StatSoft TIBCO Software Inc., Palo Alto, CA, USA). Analysis of variance (ANOVA) was used to determine the significant terms in all polynomial models.

Artificial neural networks are mathematical constructs developed according to the principle of the human brain's learning process. A big advantage of the ANN models is that no complicated mathematical formulas are needed to connect the independent and dependent variables. Multi-layer perception ANN (MLP-ANN) is considered to be the most effective type of ANN.[13,23] MLP-ANNs are built from the interdependent entities – neurons, which are organized into layers (input, hidden and output). For the purpose of developing the ANN models, the data were randomly divided into training and testing data in a ratio of 80:20. The network was trained 100,000 times with random initial values of weights and biases. The number of hidden neurons varied from 2 to 20 and was determined by the method of trial and error.

Support Vector Machine (SVM) is a supervised machine learning method which can be applied to both

Table 3 — Amount of different types of construction waste (CW) for period from 2012 to 2020

Year	CW1 (t)	CW2 (t)	CW3 (t)	CW4 (t)	CW5 (t)	CW6 (t)	CW7 (t)	CW8 (t)
2012	358969	21886	201	441	105	441	82557	229120
2013	327862	11333	71	456	28	137	66297	245100
2014	262981	25801	117	985	152	120	44041	175835
2015	254861	3758	945	243	49	89	83879	154241
2016	541088	66180	580	1892	232	254	238982	288499
2017	545156	35516	482	1106	345	332	287336	233505
2018	549343	4852	384	395	459	412	335690	178512
2019	604321	16612	1641	1257	1230	1286	327779	165615
2020	726336	9274	472	370	126	2156	478898	181887

Table 4 — Correlation matrix (Pearson (n)):

Variables	CW2	CW3	CW4	CW5	CW6	CW7	CW8
CW1	0.132	0.339	0.258	0.474	0.782	0.972	0.057
CW2		−0.070	0.888	−0.017	−0.246	−0.027	0.768
CW3			0.278	0.789	0.349	0.362	−0.404
CW4				0.394	−0.107	0.115	0.519
CW5					0.339	0.443	−0.295
CW6						0.794	−0.308
CW7							−0.130

Values highlighted in bold indicate significant deviations from zero, with a significance level of $p<0.05$

classification and regression problems.[24] In this work SVM was used for regression with 1 independent and 1 dependent variable. The selection of SVM parameters involved a process of hyperparameter tuning, where different values are tested and evaluated based on model performance metrics. This tuning was based on previous empirical knowledge[31] and cross-validation techniques implemented in TIBCO STATISTICA routine, to find the best-performing parameters. For that purpose, Regression type 1 (C = 10.000, epsilon = 0.10) with Kernel type – Radial Basis Function (gamma = 1.000) was used. The total number of iterations of the SVM model is 10,000.

Models Verification

In order to determine goodness of fit, the following statistical parameters were calculated: Reduced chi-square (x^2) (Eq. (1)), root mean square error (*RMSE*) (Eq. (2)), coefficient of determination (R^2), mean bias error (*MBE*) (Eq. (3)) and mean percentage error (*MPE*) (Eq. (4)).

$$\boldsymbol{x^2 = \frac{\sum_{i=1}^{N}(x_{pre,i}-x_{exp,i})^2}{N-n}} \quad \dots (1)$$

$$RMSE = \left[\frac{1}{N}\sum_{i=1}^{N}(x_{pre,i}-x_{exp,i})^2\right]^{1/2} \quad \dots (2)$$

$$MBE = \frac{1}{N}\sum_{i=1}^{N}(x_{pre,i}-x_{exp,i}) \quad \dots (3)$$

$$MPE = \frac{100}{N}\cdot\sum_{i=1}^{N}\left(\frac{|x_{pre,i}-x_{exp,i}|}{x_{exp,i}}\right) \quad \dots (4)$$

where, $x_{exp,i}$ and $x_{pre,i}$ were experimental and predicted values, N and n are the number of observations and constants

Results and Discussion

Results of Annual Amount of Construction Waste

The results for the annual amount of different types and total construction waste (CW1–CW8) in the period from 2012 to 2020 are shown in Table 3. It can be seen that the amount of total construction waste (CW1) in the period from 2012 to 2015 slightly decreased, and then from 2016 it had an increasing trend. The amounts of individual CW categories varied from year to year and no consistent trend could be observed. Also, it was noted that types of construction waste CW2, CW7 and CW8 had a significantly higher share in the total waste, compared to types CW3, CW4, CW5 and CW6.

The largest amount of total CW was generated in 2020 and the smallest in 2015. The average total amount of CW for the observed period was 463435.2 tons. The average amount of CW2, CW7, and CW8, as the most predominant categories in terms of quantity of the total amount of waste, was 21690.2, 216162.1, and 205812.6 tons, respectively.

Principal Component Analysis (PCA)

Pearson's correlation coefficients among various types of construction waste are illustrated in Table 4,

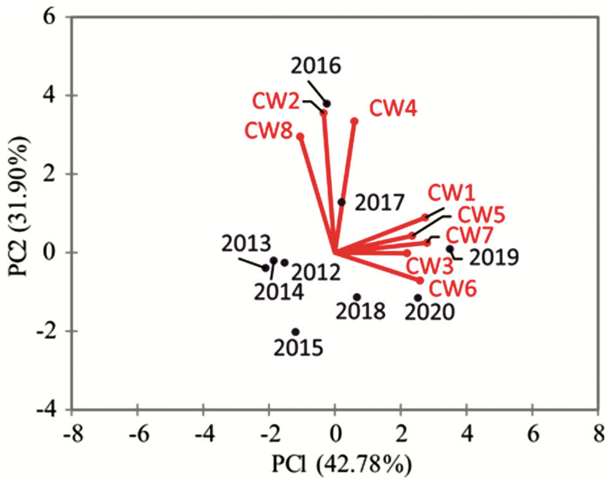

Fig. 1 — Variables (type of construction waste) and cases (years) in PC1 vs. PC2 plane

indicating a significant positive correlation ($p < 0.05$) between specific pairs of waste types: CW1 vs. CW6 and CW7, CW2 vs. CW4 and CW8, CW3 vs. CW5, CW6 vs. CW7.

PCA was conducted on the data from Table 3 to uncover patterns in the distribution of individual data points within a multidimensional space, aiming to discern inherent structures within the original dataset. The obtained results are shown in Fig. 1. The first two Principal Components (PCs) represented 74.68% of the initial variability of the data (PC1 – 42.78% and PC2 – 31.90%). PC1 was positively correlated with CW1, CW3, CW5, CW6 and CW7, while PC2 was positively correlated with CW2, CW4 and CW8. The years 2012, 2013 and 2014 form one group in the PC1 vs. PC2 plane. In 2016, CW2, CW4, and CW8 had the highest values, while CW1, CW3, CW5, CW6, and CW7 had the highest values in 2019 or 2020.

Mathematical Models

Polynomial Models

Forty polynomial models were created, encompassing five models for each construction waste type. The regression parameters of these polynomial models along with their statistical significance are displayed in Table S1. The results of the ANOVA conducted on these models are presented in Table 5. Notably, all constructed models exhibited statistical significance at a level of $\alpha = 0.05$.

Graphs comparing predicted values against observed values for the quantities of eight construction waste types for the developed polynomial models are illustrated in Fig. 2. It can be observed that among all waste categories, data predicted by model M1 had the largest deviations from actual data. The other polynomial models (M2–M5) provided better fitting of predicted and actual data, and all of them were similar in performance. None of them stood out as better than the others in predicting construction waste data for all categories.

Artificial Neural Network (ANN)

The outcomes derived from the constructed ANN models, encompassing both the total annual volume and individual category-wise annual amounts of construction waste, are presented in Table 6. Across all ANN models, the error function employed was the Sum of Squares (SOS), and the training algorithm utilized was the Broyden–Fletcher–Goldfarb–Shanno algorithm (BFGS). The hidden layer's neuron counts varied, ranging from 2 to 8, contingent upon the specific construction waste type. The training performance, as indicated by coefficient of correlation values, spanned from 0.469 to 0.992. Notably, the ANNs developed for CW1, CW6, and CW7 exhibited the most favorable training performance (> 0.9), suggesting their potential for accurately predicting the quantities of these waste types. Conversely, the training performance of ANNs for other construction waste types notably fell below (< 0.75).

The reason for this may be the currently small amount of available data on the amounts of different types of construction waste. With the collection of data in the following period and the increase of the database on construction waste, the performance of the developed ANNs can be significantly increased. The actual vs. predicted data obtained by ANNs on the amount of construction waste are illustrated in Fig. 2.

Support Vector Machine (SVM)

The quantities of construction waste across different years were modeled using the Support Vector Machine (SVM), which presents several advantages in nonlinear modeling for optimization and solution discovery. For CW1, CW2, CW3, CW5, and CW8, the number of Support Vectors (SVs) obtained was 6, while for CW4, CW6, and CW7, it stood at 5. The vector values, weighting coefficients and decision constant in the SVM models are listed in Table 7 for all types of construction waste. Observed vs. predicted values of construction waste amount by the SVM models are also shown in Fig. 2.

Table 5 — ANOVA of polynomial model of different construction waste

Construction waste type	Model	SS	DF	F-value	p-value
CW1	M1	3.87E+12	2	358.11	<0.05
	M2	3.89E+12	3	282.94	<0.05
	M3	3.88E+12	4	157.39	<0.05
	M4	3.89E+12	5	145.33	<0.05
	M5	3.89E+12	6	110.79	<0.05
CW2	M1	8.30E+09	2	14.31	<0.05
	M2	9.29E+09	3	12.90	<0.05
	M3	9.29E+09	4	8.98	<0.05
	M4	9.29E+09	5	6.63	<0.05
	M5	9.29E+09	6	5.07	<0.05
CW3	M1	6.46E+06	2	29.92	<0.05
	M2	6.48E+06	3	18.90	<0.05
	M3	6.48E+06	4	13.16	<0.05
	M4	6.48E+06	5	9.72	<0.05
	M5	6.46E+06	6	7.30	<0.05
CW4	M1	1.15E+07	2	28.51	<0.05
	M2	1.22E+07	3	25.29	<0.05
	M3	1.22E+07	4	17.62	<0.05
	M4	1.22E+07	5	13.01	<0.05
	M5	1.22E+07	6	9.95	<0.05
CW5	M1	2.50E+06	2	20.50	<0.05
	M2	2.51E+06	3	12.92	<0.05
	M3	2.50E+06	4	9.00	<0.05
	M4	2.50E+06	5	6.64	<0.05
	M5	2.51E+06	6	5.09	<0.05
CW6	M1	8.25E+06	2	23.13	<0.05
	M2	1.06E+07	3	162.65	<0.05
	M3	1.06E+07	4	113.81	<0.05
	M4	1.06E+07	5	84.65	<0.05
	M5	1.06E+07	6	64.47	<0.05
CW7	M1	1.05E+12	2	245.21	<0.05
	M2	1.06E+12	3	205.26	<0.05
	M3	1.06E+12	4	106.96	<0.05
	M4	1.06E+12	5	105.39	<0.05
	M5	1.06E+12	6	80.37	<0.05
CW8	M1	7.24E+11	2	258.26	<0.05
	M2	7.24E+11	3	165.53	<0.05
	M3	7.24E+11	4	111.94	<0.05
	M4	7.24E+11	5	85.14	<0.05
	M5	7.24E+11	6	65.01	<0.05

SS –Sum of squares
DF – Degree of freedom

Goodness of Fits

The verification of the model was performed after modeling. Model validation is possibly the most important step in the model building sequence. A high R^2 value does not guarantee that the model fits the data well. The residuals from a fitted model are the differences between the responses observed and the corresponding prediction of the response computed using the regression function. The residual analysis of model was also performed in order to check assumptions of independence, normality, homoscedasticity and zero mean of errors. The parameters of statistical test "goodness of fits" (χ^2, *MBE*, *RMSE*, *MPE* and R^2) for all developed models are shown in Table S2. The results of the residual analysis of the developed models were also listed in Table S2. Skewness gauges the degree of asymmetry within a distribution. The farther the skew value is from zero, the greater the deviation of the distribution

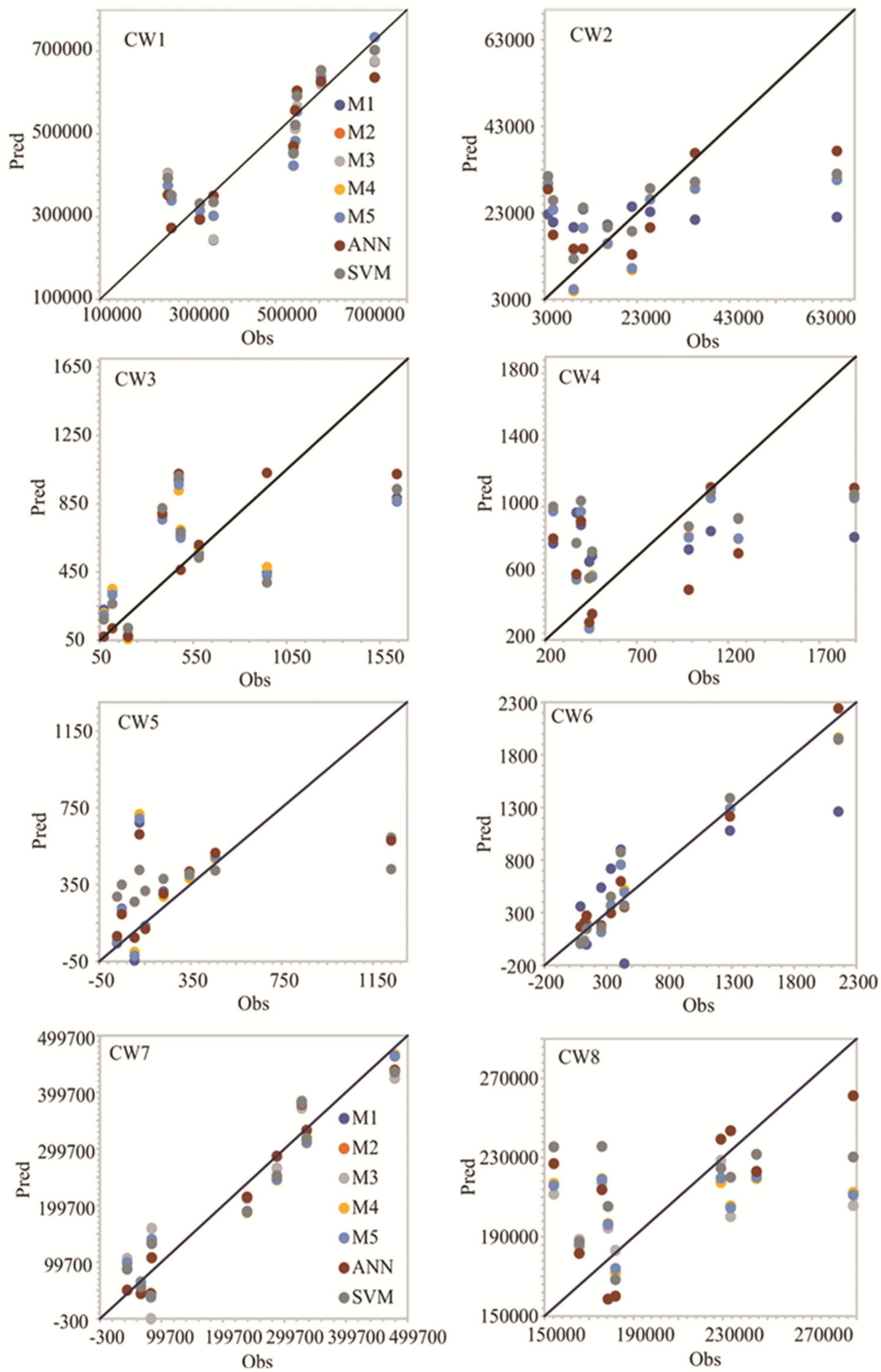

Fig. 2 — Plots of predicted vs. observed amount of eight types of construction waste (CW1–CW8) for developed polynomial models (M1–M5), ANN and SVM

from symmetry, which is characteristic of a normal distribution. Meanwhile, kurtosis measures the "peakedness" of a distribution. A non-zero kurtosis value suggests that the distribution is either flatter or more peaked compared to a standard normal distribution, which has a kurtosis value of zero.

High R^2 values indicate that the variation in the data was taken into account and that the data fitted the

Table 6 — Results of ANN

	Net. name	Training perf.	Test perf.	Training error	Test error	Training algorithm	Error function	Hidden activation	Output activation
CW1	MLP 1-3-1	0.932	0.854	1.96E+09	5.38E+07	BFGS 97	SOS	Logistic	Identity
CW2	MLP 1-4-1	0.577	0.529	1.37E+08	1.86E+07	BFGS 42	SOS	Tanh	Tanh
CW3	MLP 1-6-1	0.731	0.648	6.15E+04	4.31E+03	BFGS 62	SOS	Tanh	Logistic
CW4	MLP 1-8-1	0.469	0.338	1.27E+05	4.56E+03	BFGS 22	SOS	Tanh	Exponential
CW5	MLP 1-2-1	0.605	0.561	4.95E+04	1.58E+03	BFGS 16	SOS	Tanh	Tanh
CW6	MLP 1-3-1	0.992	0.886	5.99E+03	2.27E+03	BFGS 15	SOS	Logistic	Identity
CW7	MLP 1-7-1	0.982	0.839	4.18E+08	3.70E+08	BFGS 17	SOS	Tanh	Exponential
CW8	MLP 1-8-1	0.636	0.527	6.50E+08	5.19E+07	BFGS 48	SOS	Logistic	Tanh

Table 7 — Vector values of the developed SVM models

	Vector No.	1	2	3	4	5	6	Decision Constant
CW1	Weights	0.42	10.00	−9.42	−10.00	10.00	−1.00	−1.05
	SV	0.00	0.17	0.33	0.50	0.83	1.00	
CW2	Weights	6.17	−10.00	10.00	−10.00	10.00	−6.17	0.29
	SV	0.00	0.17	0.33	0.50	0.83	1.00	
CW3	Weights	9.17	−10.00	−10.00	10.00	8.66	−7.83	0.53
	SV	0.00	0.17	0.33	0.50	0.83	1.00	
CW4	Weights	−3.70	10.00	−10.00	10.00	−6.30	—	0.75
	SV	0.17	0.33	0.50	0.83	1.00	—	
CW5	Weights	5.14	−10.00	10.00	−10.00	2.37	2.49	−0.58
	SV	0.00	0.17	0.33	0.50	0.83	1.00	
CW6	Weights	10.00	−8.13	−10.00	10.00	−1.87	—	−1.25
	SV	0.00	0.17	0.50	0.83	1.00	—	
CW7	Weights	6.88	−5.37	−10.00	10.00	−1.52	—	−0.68
	SV	0.17	0.33	0.50	0.83	1.00	—	
CW8	Weights	0.88	10.00	−7.36	−10.00	10.00	−3.52	−0.62
	SV	0.00	0.17	0.33	0.50	0.83	1.00	

developed model well. Accordingly, R^2 was taken as the main parameter for assessing the quality of the developed models and their predictive capabilities. Types of construction waste CW1, CW6 and CW7 had high values of R^2 (> 0.75) for all developed models (except CW6 for model M1), while for other types of construction waste the value of R^2 was much lower. Performance of the models with low R^2 values can be improved by increasing the construction waste data set in the future. When considering the R^2 values within each type of construction waste, it can be seen that the ANN models had the highest R^2, while the M1 models had the lowest R^2 values for all types of CW. This leads to the conclusion that ANN models have the greatest potential for predicting the amount of generated construction waste in the coming years.

Conclusions

In this research, data on the amount of different types of construction waste were modeled, whereby 7 models were developed for each type - 5 polynomial, ANN and SVM models. All models developed for the total amount of construction waste, as well as for the amount of wood and mineral waste from construction and demolition, had high R^2 values, indicating that they have the potential to be used to successfully predict the amount of this waste that will be generated in the following period.

Elevated R^2 values signify that the model effectively described data variance and aligned well with the developed model. Consequently, R^2 was the primary metric used to evaluate the quality and predictive capacity of the models created. Construction waste types CW1, CW6, and CW7 exhibited high R^2 values (> 0.75) across all models (except CW6 for model M1), while other waste types showcased notably lower R^2 values. Enhancing the dataset related to these low R^2 models could significantly boost their performance in the future. Looking within each construction waste type, the ANN models consistently yielded the highest R^2 values, contrasting with the M1 models, which consistently produced the lowest R^2 values across all CW types. This underscores the potential of ANN models in accurately predicting the forthcoming volume of generated construction waste.

Developed ANN models have generally proven to be the best for all types of construction waste, so in further work the focus should primarily be on their development and improvement with increasing data on construction waste.

Supplementary Data

Supplementary data associated with this article is available in the electronic form at https://nopr.niscpr.res.in/jinfo/jsir/JSIR_83(5)557-566_SupplData.pdf

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