


Article

Predictive Analysis of Municipal Solid Waste Generation Using an Optimized Neural Network Model

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Abstract: Developing successful municipal waste management planning strategies is crucial for implementing sustainable development. The research proposed the application of an optimized artificial neural network (ANN) to forecast quantities of waste in Poland. The neural network coupled with particle swarm optimization (PSO) algorithm is compared to the conventional neural network using five assessment metrics. The metrics are coefficient of efficiency (CE), Pearson correlation coefficient (R), Willmott's index of agreement (WI), root mean squared error (RMSE), and mean bias error (MBE). Selected explanatory factors are incorporated in the developed models to reflect the influence of economic, demographic, and social aspects on the rate of waste generation. These factors are population, employment to population ratio, revenue per capita, number of entities by type of business activity, and number of entities enlisted in REGON per 10,000 population. According to the findings, the ANN-PSO model (CE = 0.92, R = 0.96, WI = 0.98, RMSE = 11,342.74, and MBE = 6548.55) significantly outperforms the traditional ANN model (CE = 0.11, R = 0.68, WI = 0.78, RMSE = 38,571.68, and MBE = 30,652.04). The significant level of the reported outputs is evaluated using the Wilcoxon-Mann-Whitney U-test, with a significance level of 0.05. The *p*-values of the pairings (ANN, observed) and (ANN, ANN-PSO) are all less than 0.05, suggesting that the models are statistically different. On the other hand, the *P*-value of (ANN-PSO, observed) is more than 0.05, suggesting that the difference between the models is statistically insignificant. Therefore, the proposed ANN-PSO model proves its efficiency at estimating municipal solid waste quantities and may be regarded as a cost-efficient method of developing integrated waste management systems.

Keywords: predictive modelling; trend analysis; municipal solid waste; particle swarm optimization; hybrid neural network



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1. Introduction

Municipal solid waste (MSW) has emerged as a new challenge to the United Nations' global sustainability strategy [1–3]. MSW is defined as garbage generated in houses or other sources that contains no hazardous chemicals [4]. The MSW accumulation problem has been worrying both local and international policymakers and stakeholders, posing serious health and environmental problems [5]. Nearly 2.01 billion tonnes of MSW are generated annually all over the world, with a projected increase of 3.40 billion tonnes by 2050 [6]. Most of the countries in the Middle East/North Africa (MENA) region are known for high MSW generation, with waste output exceeding 2 kg per capita per day on average [7]. In

2019, the European Union (EU) generated a total of 502 kg of MSW per capita. Concerning the per capita MSW generation, Denmark and Luxembourg produced the highest rates of 844 and 791 kg per inhabitant, whilst Romania produced the lowest rate of 280 kg per inhabitant in the EU [8]. The annual household waste output in Polish cities is reported to range between 238 and 315 kg per inhabitant [9]. According to the Central Statistical Office, the amount of waste increased from 10,040,108 Mg/year to 12,752,778.17 Mg/year between 2010 and 2019 [10]. This implies that the amount of waste produced in Poland is steadily increasing. The volumes of wastes are predicted to continue to rise owing to expanding urbanization, rising standard of living, and changing social behavior and habits. This issue is becoming of great importance in Poland, not only because of the growing amount but also because of the lack of an effective waste management system and the associated negative environmental impact of wastes [11].

An accurate prediction of the MSW generation rate is critical for sustainable and efficient MSW management [1,12–14]. Forecasting is a decision-making method that captures the trend of historical and current information to be used for future projections [15,16]. It has been used by many stakeholders such as academics, policymakers, government organizations, and municipalities to develop sustainable and effective MSW management [17–19]. Geographic location, seasonal fluctuations, increased industrialization and urbanization, economic conditions, existing regulations, recovery and reuse restrictions, waste management infrastructure (collection, recycling facilities, incinerators, or landfill), site procedures, growing population, people habits, and lifestyle are all variables that influence the quantity of generated wastes [20–22]. The availability of solid historical data will aid in anticipating the generated quantity of MSW in the future and implementing the circular economy to reuse waste materials [23–25]. This will aid in avoiding the exploitation of limited natural resources, creating more jobs, enhancing the national economy, and minimizing negative environmental repercussions [2].

As a result, building a reliable MSW forecasting model is crucial to anticipate the generated quantity of MSW, which can be used for developing waste management infrastructures and optimizing waste management frameworks [26,27]. Examples of the forecasting techniques are artificial intelligence methods, time series analysis, material flow analysis, and statistical analysis [26,28]. Artificial intelligent techniques have been popular in implementing waste management models. Meza et al. [29] examined three artificial intelligence-based models for forecasting the generation rate of urban solid waste in the city of Bogota, Colombia. A viable decision-making approach was investigated in this study to plan and develop technologies for waste collection, transportation, and final disposal in cities. The decision tree was the first applied machine learning algorithm to model data separation constraints based on learning decision rules on the input features. The second approach used was a support vector machine (SVM) that could deal with highly variable data and a limited amount of training data. Finally, a recurrent neural network model was used whose architectural design made it possible to investigate temporal connections among the same. This research took into account the population, socioeconomic stratification, quantity of solid waste generated during a set period of time, and distribution of solid waste generated per zone in the city. According to the findings, SVM was the best forecasting model with the best local trend of the points and reliability in the recorded values.

Soni et al. [28] compared different artificial intelligence models, such as the adaptive neuro-fuzzy inference system (ANFIS), artificial neural network (ANN) as well as the ANFIS and ANN coupled with discrete wavelet theory (DWT) and genetic algorithm (GA) to assess their capacity to estimate the amount of generated waste in the city of New Delhi, India. For each model, the root mean square error (RMSE), coefficient of determination (R^2), and index of agreement (WI) values were computed to compare the models. The hybrid ANN–GA model was proved to be the most accurate among the six models because it yielded the lowest RMSE (95.7) and the highest R^2 (0.87) and WI (0.864) values. Dissanayaka and Vasanthapriyan [30] developed a prediction model for forecasting future MSW generation in Sri Lanka using nonlinear, linear, and machine

learning approaches. The correlation among the relevant factors was evaluated using principal component analysis and Pearson correlation. The employed machine learning models included ANN, random forest, and regression analysis. The correlation coefficients of $R^2 = 0.6973$, $R^2 = 0.9608$, and $R^2 = 0.9923$ were reported for linear regression, random forest, and ANN, respectively. Therefore, ANN outperformed linear regression and random forest models in terms of accuracy.

Kulisz and Kujawska [9] applied neural network modeling to forecast MSW in Poland. The MSW was divided into five categories: glass, biodegradable, paper and cardboard, plastics and metals, and miscellaneous waste. Selected explanatory factors were incorporated in the suggested models to reflect the influence of economic, demographic, and social aspects on the quantity of generated wastes. Different neural network models were applied by changing the number of hidden neurons from 2 to 10. The prediction accuracy of the developed models was measured using the Pearson correlation coefficient (R) and mean squared error (MSE). The ANN model with six hidden neurons showed good prediction accuracy by yielding a high R-value (i.e., 0.914) for categorized wastes. Using the statistical data from 2013 to 2019, the model projected a 2% rise in future waste output in 2024. The findings affirmed the suitability of the ANN model as a cost-efficient method for developing integrated waste management systems. Oguz-Ekim [31] modeled the MSW generation rate in Turkey using support vector regression (SVR), backpropagation neural network (BPNN), and general regression neural network. It can be concluded that SVR and BPNN techniques can be used to predict MSW generation, with BPNN marginally outperforming SVR. The developed models could be generalized in other countries across the world.

Daoud et al. [32] studied the rising problem of solid waste in the MENA area, with an emphasis on construction and demolition waste in Egypt. The study analyzed the most recent official reports, technical studies, and research papers on the subject. The key barriers to effective and efficient solid waste management systems, as well as recommendations for improvement, were compiled in this study. Policymakers, local and national governments, construction industry practitioners, and academics dealing with the challenges of solid wastes in the MENA area were likely to benefit from the findings of this study. ElSaid and Aghezzaf [33] performed a system analysis of MSW management in Cairo, Egypt. To describe an underlying model of the MSW management system, a restricted non-linear mathematical model was developed for six waste material flows (glass, cardboard and paper, metals, plastics, organic material, and others). Combinations of five treatment options were incorporated in the developed model, which included landfilling, incineration, anaerobic digestion, composting, and mechanical biological treatment. The model determined the capability of treatment techniques, as well as feasible best design solutions and recommendations. The environmental and economic effects of alternative scenarios were studied and analyzed. The gap between the current status quo and the proposed improved methods for diverting waste from landfills and reducing carbon dioxide emissions was elaborated in this study.

Ayeleru et al. [34] used ANN and SVM techniques to estimate MSW generated in the City of Johannesburg, South Africa. Furthermore, a projection was developed up to 2050 based on the gathered historical data. The research findings confirmed the effectiveness of machine learning approaches for MSW forecasting. The ANN model with 10 neurons outperformed other models, yielding an R^2 value of 0.999, whereas the linear model performed best in the SVM models, with an R^2 value of 0.986. Based on the ANN10 model, the total quantity of MSW in the City of Johannesburg was expected to reach 1.95×10^6 tonnes in 2050, with an average yearly waste of 1.78×10^6 tonnes. Coskuner et al. [35] used a multi-layer perceptron ANN to forecast the yearly generated rates of commercial, household, and construction and demolition wastes in Bahrain. The prediction models incorporated several explanatory variables to account for the impact of economic, social, geographic, demographical, and touristic aspects on waste generation rates. To assess the efficacy of the generated models, the MSE and R^2 performance metrics were employed. According to the findings, the ANN model was associated with high R^2 and low MSE values, indicating

good prediction accuracy. This demonstrated the capability of the proposed ANN model at predicting waste generation rates from a variety of sources and that it could be used to construct integrated MSW management systems.

In summary, the ANN models could be applied for modeling MSW quantities given limited data. The flexibility of neural network tools is a feature that allows for the consideration of a variety of additional factors, including economic, demographic, geographic, social, technological, legislative, and administrative, all of which may play a role in determining the final quantity of municipal wastes. Despite the excellent ability of standalone ANN models, their training algorithms may trap in local optimums or may be slow to convergence. Optimization algorithms are regarded as viable alternatives to standard training algorithms because they avoid trapping in local optimums [36,37]. However, limited research was undertaken to examine the performance of hybrid ANN models to forecast MSW generation quantities. Furthermore, it is necessary to assess the performances of pure and hybrid ANN models using numerous evaluation indices. In this regard, this research involves training and evaluating the performance of conventional and hybrid ANN models in predicting MSW quantities. Because of its high prediction accuracy and consistency over time, the ANN is coupled with the particle swarm optimization (PSO) algorithm in this research study. The capacity to estimate MSW at a city level allows local waste management organizations and government agencies to develop robust waste management strategies. In addition, the developed prediction model may be incorporated into legal laws and systems to reduce municipal waste generation rates, improve the efficiency of waste energy recovery, and improve adherence to sustainable development principles.

The major contributions of this research could be summarized as follows:

1. Incorporating the influence of economic, demographic, and social aspects on the quantity of generated wastes.
2. Estimating the waste quantities using traditional and hybrid neural network models and comparing their performances using several evaluation metrics.
3. Enhancing the performance metrics of the developed prediction models in the literature.

2. Materials and Methods

2.1. Feed-Forward Artificial Neural Network

ANN is a machine learning algorithm that is inspired by the human brain's anatomy [38]. This network is used to capture the non-linear relationship between the input and output factors. It has been widely applied in waste management problems such as the type or quantity of waste produced and its relationship to socioeconomic variables [39,40]. It has gained increasing popularity because of its unique benefits over other approaches, such as the clear network architecture, high-performance quality, and simple implementation [41–43]. Figure 1 depicts the structure of the neural network. It comprises input, hidden, and output layers. Data are supplied into the network through the input layer, and it is then processed utilizing hidden layers to get and report the desired output in the output layer. The number of neurons in the input layer is developed based on the number of input variables while the number of different outcomes determines the number of neurons in the output layer [44]. The weights and biases are assigned to channels linking neurons in subsequent layers. The activation state of the neuron is then determined by passing this value through an activation function. The data are propagated forward through activated neurons in the different layers until the result is delivered in the last layer. The network is trained by comparing the anticipated output to the actual result. The weights are then adjusted based on the computed prediction error in the back-propagation process. The forward and backward propagation procedures are repeated iteratively until the network can correctly predict the output [45].

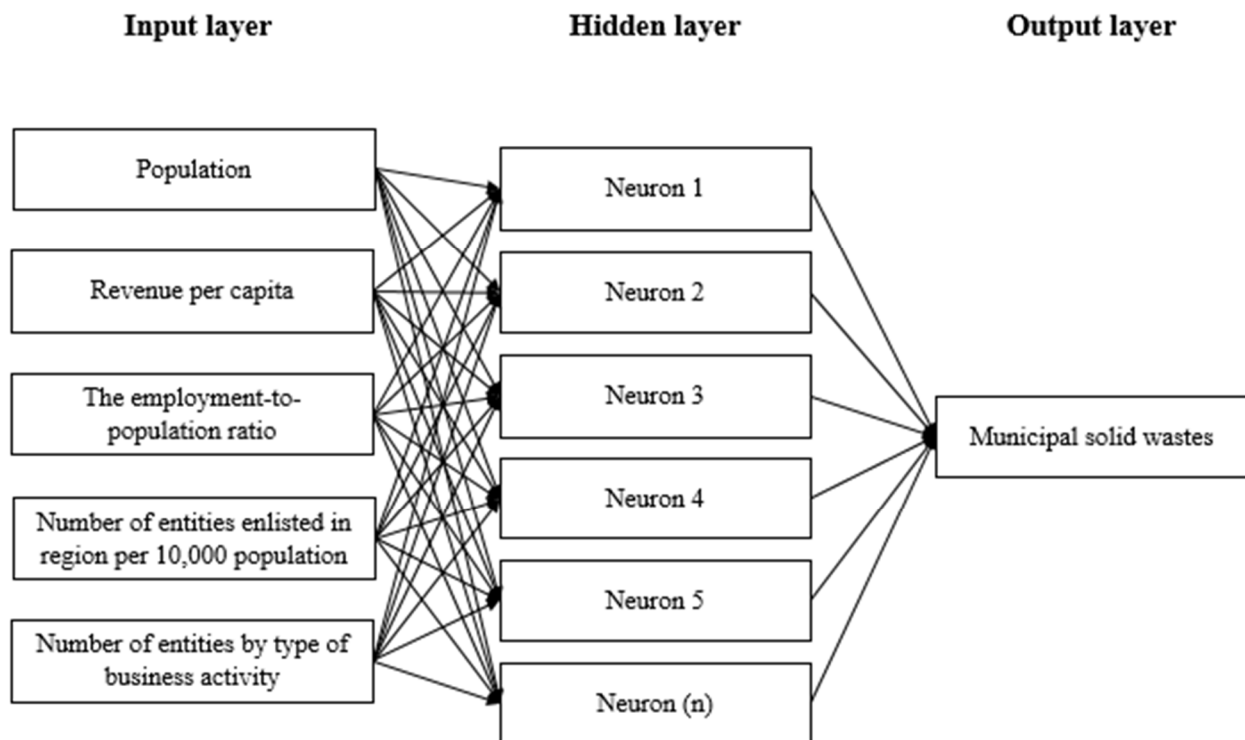


Figure 1. Structure of a neural network.

2.2. Particle Swarm Optimization Algorithm

One of the most well-known evolutionary algorithms is PSO that has been widely employed in a wide range of scientific and industrial applications [46]. The flowchart of the PSO algorithm is illustrated in Figure 2. This algorithm is based on how a school of fish or flock of birds navigates and moves. It finds a global optimum solution by populating the search space with particles where each particle has three vectors that store the present position, the moving direction, and the optimal location in the entire swarm. The ideal local position of a particle, as well as the experience of its neighbors, influence its migration. The global best position in the solution space is updated as nearby particles discover better places in the search space. This acts as a guide to assist the swarm in determining the optimal solution. Finally, the optimum solution is determined by the current best particle position in the swarm [47].

2.3. Neural Network Optimized Using Particle Swarm Optimization Algorithm

In this study, a neural network is used to forecast the MSW quantities in the different Polish cities. Optimization algorithms allow neural networks to avoid overfitting and local minima during training [48,49]. The PSO algorithm is utilized in this study to train the ANN model to figure out what the best weights and biases are. This algorithm is considered one of the most popular and effective ANN training methods [37,50]. Figure 3 depicts the flowchart of the improved ANN model. The optimization algorithm establishes the weights and calculates the fitness function to train the network. The network fitness is interpreted in this study by calculating the error as shown in Equations (1) and (2). When the global best solution, which is associated with the least error function, is found, the optimization process ends.

$$MSE(a, p) = \frac{\sum_i (a_i - p_i)^2}{n} \quad (1)$$

$$NMSE(a, p) = MSE(a, p) / MSE(a, 0) = \|a - p\|_2^2 / \|a\|_2^2 \quad (2)$$

where $NMSE$ represents the normalized mean squared error, n represents the total number of data points, and a_i and p_i represent the actual and predicted values, respectively.

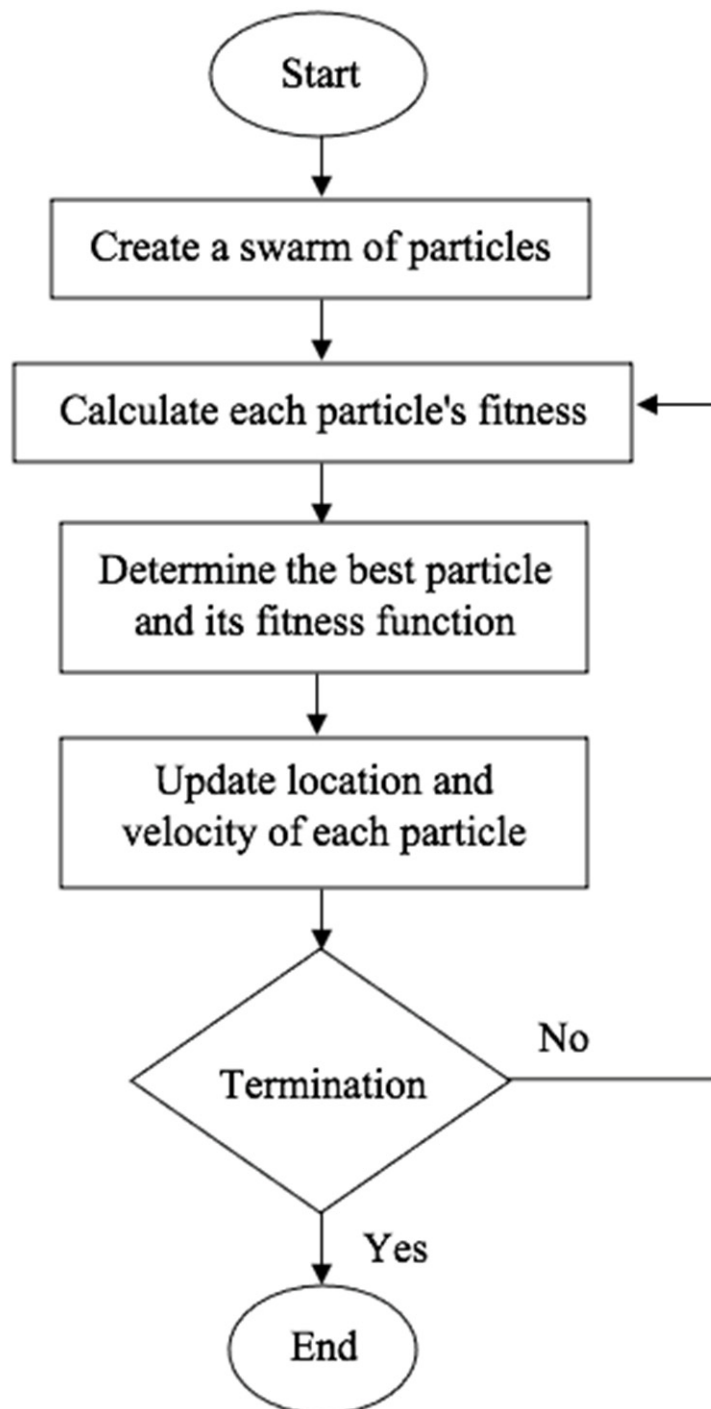


Figure 2. Flowchart of PSO algorithm.

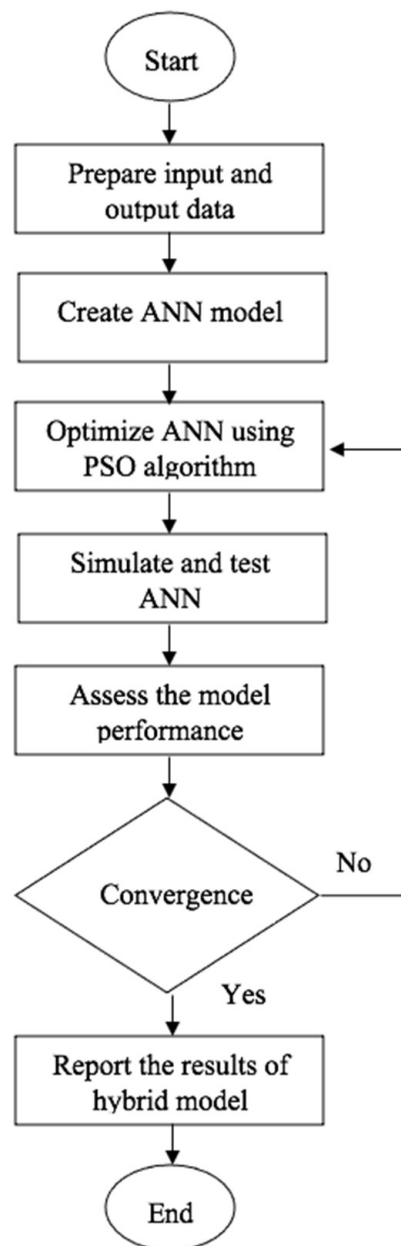


Figure 3. Flowchart of ANN model coupled with PSO algorithm.

2.4. Performance Assessment Metrics

The performance of the conventional and optimized neural network models is compared using five performance assessment criteria; coefficient of efficiency (Equation (3)), Pearson correlation coefficient (Equation (4)), Willmott's index of agreement (Equation (5)), root mean squared error (Equation (6)), and mean bias error (Equation (7)). These metrics are used for assessing the robustness of the relationship between modeled and observed data. It should be noted that higher values of the first three metrics, as well as lower values of the last two metrics, imply that the anticipated and actual values are in excellent agreement, and vice versa [51–53].

$$CE = 1 - \left[\frac{\sum_{i=1}^n (p_i - a_i)^2}{\sum_{i=1}^n (a_i - \bar{a})^2} \right] \quad (3)$$

$$R = \frac{\sum_{i=1}^n (a_i - \bar{a})(p_i - \bar{p})}{\sqrt{\sum_{i=1}^n (a_i - \bar{a})^2 \sum_{i=1}^n (p_i - \bar{p})^2}} \quad (4)$$

$$WI = 1 - \left[\frac{\sum_{i=1}^n (a_i - p_i)^2}{\sum_{i=1}^n (|p_i - \bar{a}| + |a_i - \bar{a}|)^2} \right] \quad (5)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (a_i - p_i)^2} \quad (6)$$

$$MBE = \frac{1}{n} \sum_{i=1}^n |p_i - a_i| \quad (7)$$

where \bar{p} and \bar{a} represent the average predicted and actual values.

3. Model Development

The flowchart of the proposed model is illustrated in Figure 4. The main objective of this research study is to forecast the MSW quantities in Polish cities based on socio-economic factors. For this purpose, the neural network models have been developed and their prediction performance is evaluated using five assessment metrics. Furthermore, the significance level of the outcomes delivered by the conventional and trained neural network models is determined using the Wilcoxon–Mann–Whitney U-test. Finally, the best forecasting model is suggested based on the reported results and findings.

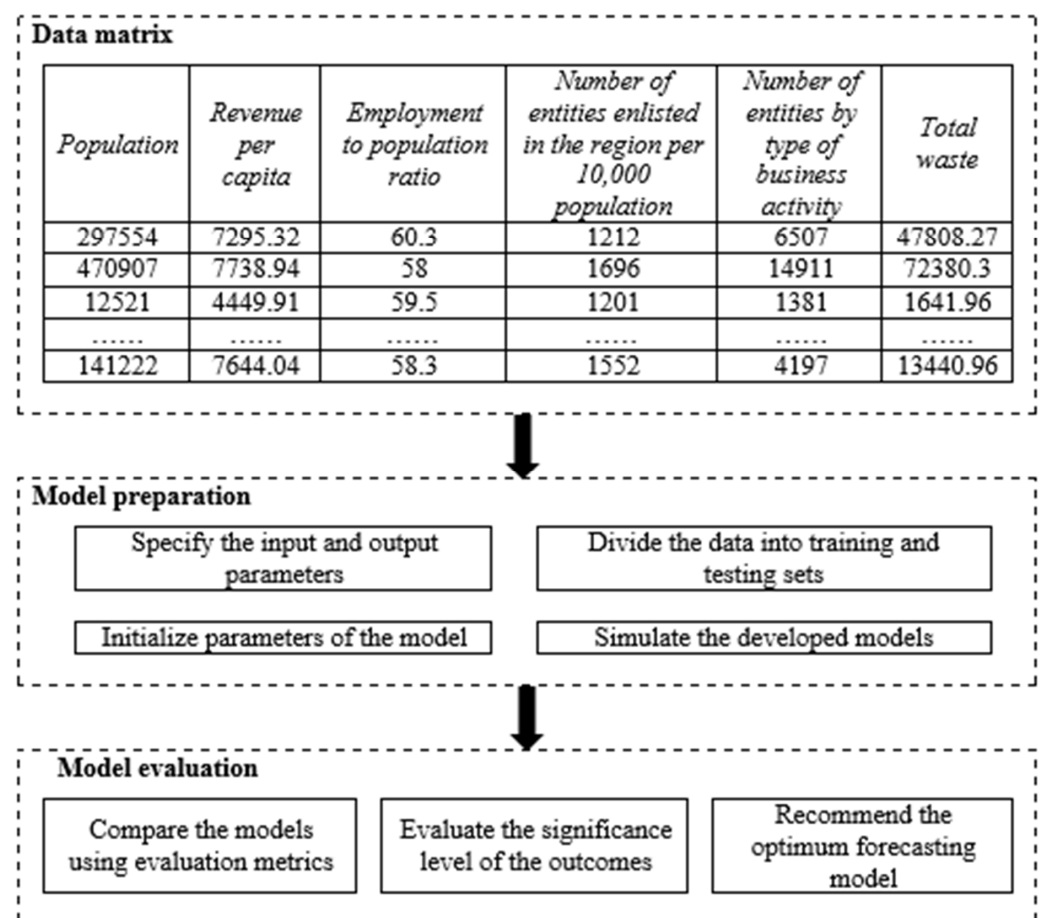


Figure 4. Components of the proposed framework.

4. Case Study

The data used in this research is acquired from a previous research study in Poland [9]. The waste generation characteristics of many cities with varying social and economic aspects in 2019 are provided in Table 1. The input factors comprise population (capita), revenue per capita, employment to population ratio (%), number of entities enlisted in the official national register of business entities (REGON) per 10,000 population, and number of entities by type of business activity while the output factor refers to the total MSW quantities. MSW volume is found to be positively and substantially correlated with population and income level in research studies [54]. This can be attributed to the fact that rapid population growth increases the amount of waste generated. Moreover, individuals in the affluent class consume more than those in the lower-income class, leading to an increased rate of waste generation for the former [55]. The unemployment rate impacts the population's purchasing power, which could have a direct impact on waste disposal levels [56]. Finally, the number of entities and type of business activity (e.g., construction, industrial) in each entity impact the quantity and composition of generated waste [4].

Table 1. Description of the dataset.

Cities	Population (Capita)	Revenue per Capita	The Employment-to-Population Ratio (%)	Number of Entities Enlisted in REGON per 10,000 Population	Number of Entities by Type of Business Activity	Total Waste (Mg)
Białystok	297,554	7295.32	60.3	1212	6507	47,808.27
Gdańsk	470,907	7738.94	58	1696	14,911	72,380.3
Głubczyce	12,521	4449.91	59.5	1201	1381	1641.96
Jastrowie	8633	4906.28	59.1	902	208	465
Katowice	292,774	7437.27	58.6	1655	7186	36,130.85
Kraków	779,115	7630.02	59.1	1886	22,854	89,286.4
Krotoszyn	28,804	4691.94	60	1114	731	2948.04
Legnica	99,350	6310.35	58.9	1393	2511	10,115.84
Lublin	33,784	6941.85	58.6	1359	7546	88,045
Łódź	679,941	6600.84	56.4	1384	17,303	104,336.69
Małomice	3458	4864.37	62.4	856	92	173.33
Oles'nica	1839	5821.09	58.4	1164	890	167.35
Olsztynek	7514	5004.64	62.1	954	132	352.33
Poznań	534,813	7766.51	58.1	2158	18,365	80,565.32
Rzeszów	196,208	7533.14	60.1	1496	4340	26,543.42
Ślupsk	90,681	6855.05	58	1405	2203	7670.48
Staszów	14,649	4622.92	59.8	969	657	1073.06
Suwałki	69,758	7502.33	62	1016	1399	3833.76
Szczecin	401,907	6563.2	58.3	1721	14,428	42,518.5
Toruń	201,447	6385.79	59	1313	4606	18,329.87
Warszawa	1,790,658	10,154.88	57.3	2548	60,948	129,111.64
Wrocław	642,869	7681.46	58.6	1909	19,714	111,090.3
Zakopane	27,010	6325.61	58	2280	785	3319.14
Zamość	63,437	7538.2	59.8	1190	1193	6516.2
Zielona Góra	141,222	7644.04	58.3	1552	4197	13,440.96

The distribution of MSW quantities and waste per capita (total MSW quantities divided by population) in Polish cities is visualized in Figure 5. It is worth noting that Warszawa city is the most densely populated city (i.e., 1,790,658 persons) and it generates the highest quantities of wastes (i.e., 129,111.64 Mg). On the contrary, Oles'nica city has the lowest population density of 1839 persons and it is associated with the lowest quantities of wastes (i.e., 167.35 Mg). Meanwhile, Lublin city is characterized by the highest waste per capita of 2.61 Mg/person. Table 2 depicts the statistical data on MSW, which illustrates that the wastes do not follow the normal distribution and are rather right-skewed due to their positive skewness value.

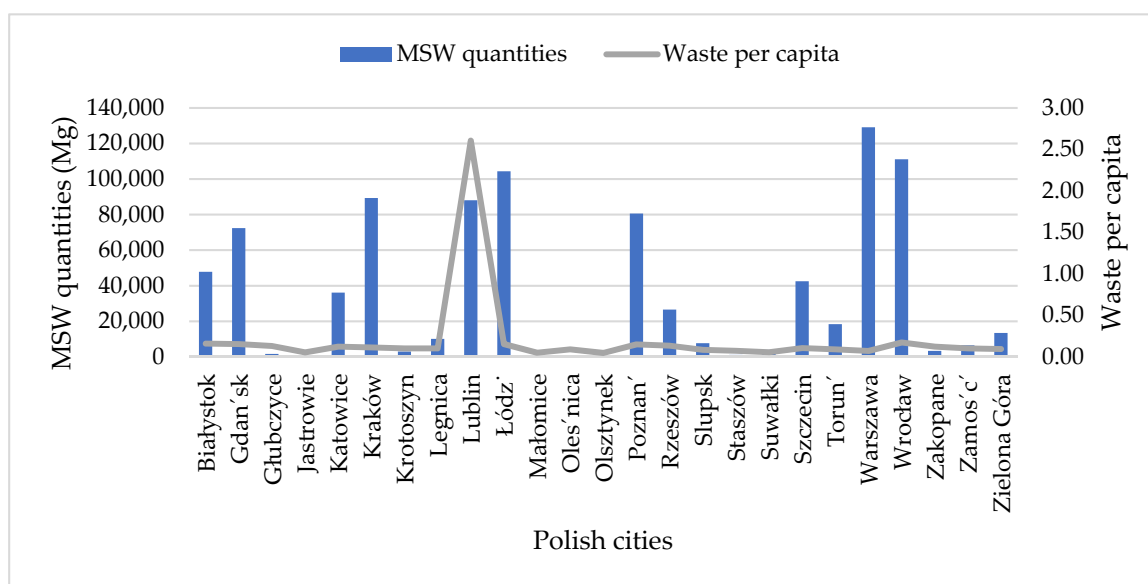


Figure 5. Distribution of municipal wastes in Polish cities.

Table 2. Statistical parameters of input and output parameters for MSW prediction.

Statistical Parameters	Population	Revenue per Capita	The Employment-to-Population Ratio	Number of Entities Enlisted in REGON per 10,000 Population	Number of Entities by Type of Business Activity	Total MSW (Mg)
Median	99,350.0	6855.1	58.9	1384.0	4197.0	13,441.0
Standard deviation	395,943.5	1352.4	1.4	443.5	13,022.0	41,816.4
Mean	275,634.1	6650.6	59.1	1453.3	8603.5	35,914.6
Min	1839.0	4449.9	56.4	856.0	92.0	167.4
Max	1,790,658.0	10,154.9	62.4	2548.0	60,948.0	129,111.6
Skewness	2.6	0.2	0.8	0.8	3.0	1.0
Kurtosis	8.4	0.4	0.6	0.2	10.8	-0.5

Figure 6 shows the correlation between all of the factors used to forecast municipal wastes. Variables having correlation coefficients between 0.5 and 0.7 can be classified as moderately correlated. This is true for the following pairs: revenue per capita and wastes, and number of entities enlisted in REGON per 10,000 population and wastes. In addition, variables with correlation coefficients of 0.7 to 0.9 have a strong correlation. This is true for the variables of population and revenue per capita, population and number of entities enlisted in REGON per 10,000 population, population and total wastes, revenue per capita and number of entities enlisted in REGON per 10,000 population, revenue per capita and number of entities by type of business activity, number of entities enlisted in REGON per 10,000 population and number of entities by type of business activity, and number of entities by type of business activity and total wastes. Furthermore, the population and employment to population ratio, revenue per capita and employment to population ratio, employment to population ratio and number of entities enlisted in REGON per 10,000 population, employment to population ratio and number of entities by type of business activity, and employment to population ratio and waste quantities variables have an inversely proportionate relationship. Finally, the population is correlated to the largest extent with the number of entities by type of business activity.

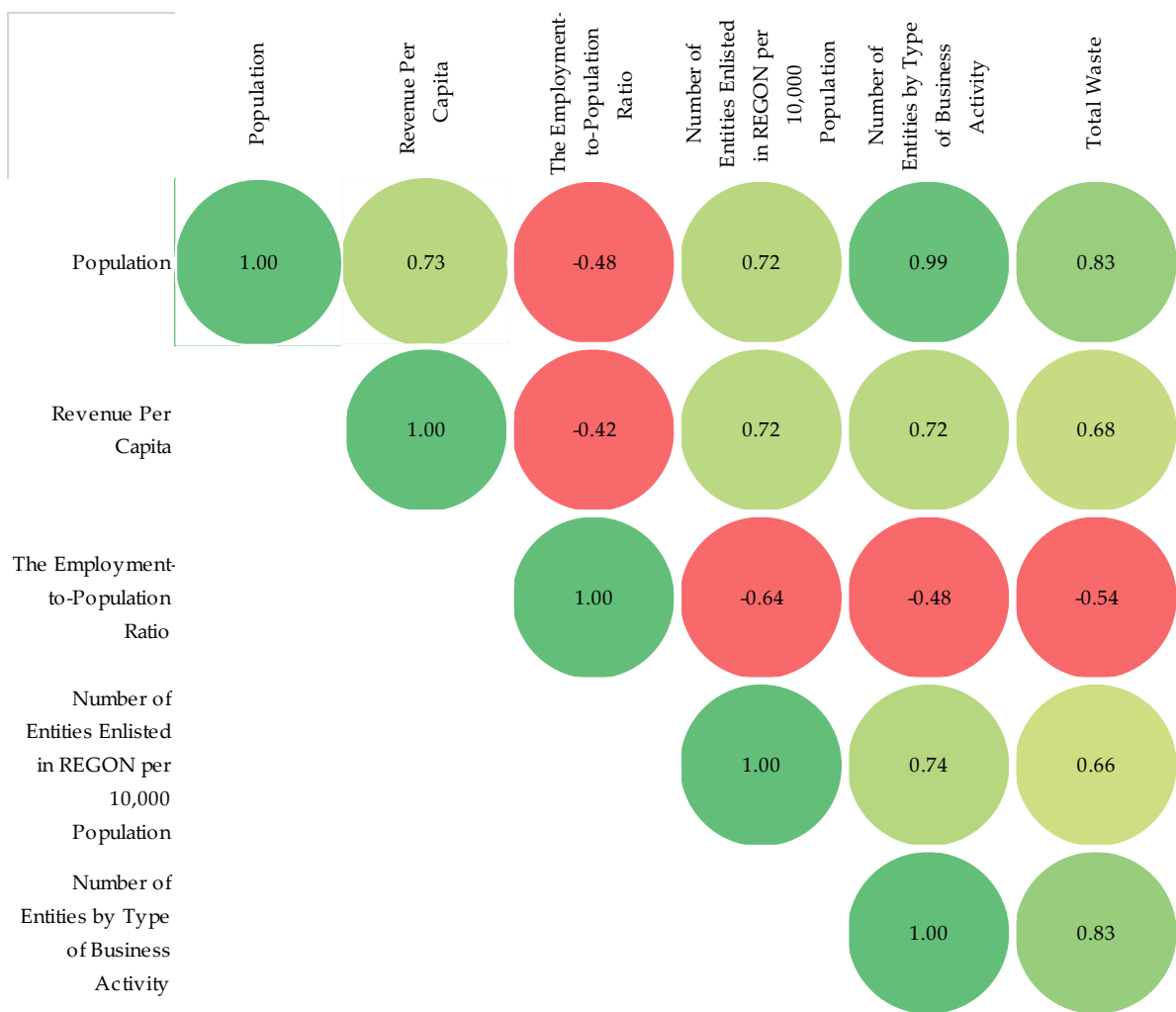


Figure 6. Correlation between input and output parameters for MSW prediction.

5. Results

The ANN parameters have to be specified such that the number of hidden neurons is estimated to be 10. The same number of hidden neurons is assumed for the ANN–PSO model in order to provide a fair evaluation of the models. For PSO, the maximum number of iterations and population size are assumed to be 200 and 50, respectively. Furthermore, the inertia weight, inertia weight damping ratio, personal learning coefficient, and global learning coefficient are determined to be 1, 0.99, 2, and 2, respectively. Finally, the MATLAB R2019a software is used to develop the neural network models.

Figure 7 shows a comparison between anticipated and actual MSW quantities in Poland. As shown in Table 3, there are five different metrics used to evaluate the performance of neural network models, namely CE, R, WI, RMSE, and MBE. The greatest CE, R, and WI are indicative of a model's best performance. In addition, the best models are associated with the least values of RMSE and MBE values. The CE values of ANN and ANN–PSO models are 0.11 and 0.92, respectively. ANN and ANN–PSO models have R values of 0.68 and 0.96, respectively. ANN–PSO performs better in terms of WI, similar to CE and R findings. For example, ANN and ANN–PSO models have WI values of 0.78 and 0.98, respectively. With respect to the error metrics, ANN–PSO is associated with RMSE of 11,342.74 and MBE of 6548.55, significantly lower than that of the ANN model (RMSE = 38,571.68 and MBE = 30,652.04). This demonstrates that the ANN model trained using the PSO algorithm outperforms the traditional ANN model. As a result, the

ANN-PSO model may be recognized as a reliable model for forecasting MSW quantities in Poland based on social and economic aspects.

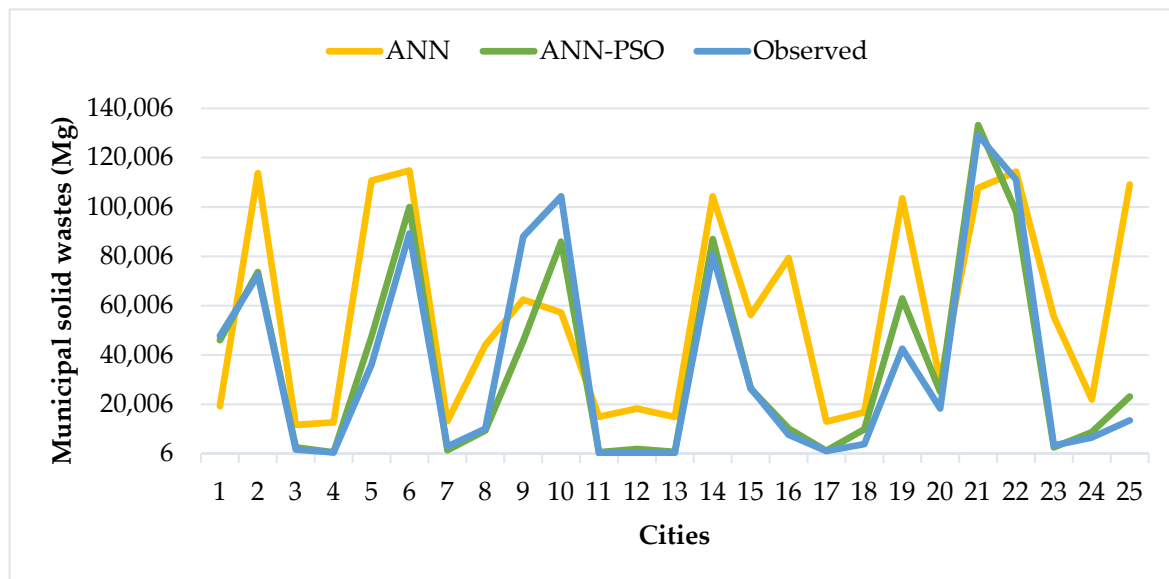


Figure 7. Time series plot of the actual and predicted MSW.

Table 3. Assessment performance metrics of the neural network models.

Performance Measure	Neural Network Model	
	ANN	ANN-PSO
CE	0.11	0.92
R	0.68	0.96
WI	0.78	0.98
RMSE	38,571.68	11,342.74
MBE	30,652.04	6548.55

The significant level of the neural network models' output is evaluated using the Wilcoxon–Mann–Whitney U-test, with a significance level of 0.05. The test validates the null hypothesis, which asserts that the two rankings are equal. The alternative hypothesis, on the other hand, indicates that the two models are ranked differently. The null hypothesis is rejected in favor of the alternative hypothesis if the p -value is less than the significance level. The null hypothesis is accepted if the p -value is larger than the degree of significance. The p -value of (ANN-PSO, observed) is more than 0.05, suggesting that the difference between the models is statistically insignificant (i.e., null hypothesis is true). The p -values of the pairings (ANN, observed) and (ANN, ANN-PSO) are all less than 0.05, suggesting that the models are statistically different (i.e., null hypothesis is false).

The outcomes of the proposed ANN-PSO model are compared to the results reported in the literature, as summarized in Table 4. For the goal of making short-term weekly predictions, Noori et al. [39] used ANN and principal component regression to estimate MSW output in Tehran. The ANN had R and average absolute relative error (AARE) values of 0.837 and 0.044, respectively. These metrics were considered better than that of the principal component regression (R = 0.445 and AARE = 0.066). Furthermore, Kulisz and Kujawska [9] forecasted the MSW (glass, biodegradable, plastics and metals, paper and cardboard, and other waste) generation rate in Poland by developing an ANN model. The model accounted for the influence of economic, demographic, and social parameters on waste generation quantities. The model exhibited high prediction accuracy by acquiring a high R-value (R = 0.914) and low MSE value.

Table 4. Comparison of the outcomes of this research against the results reported in the literature.

Application Area	Case Study	Performance Metrics	References
Predicting MSW (glass, biodegradable, plastics and metals, paper and cardboard, and other waste) generation amounts using ANN	Different polish cities	R = 0.914	[9]
Estimating weekly MSW output using ANN	Tehran	R = 0.837 and AARE = 0.044	[39]
Long-term prediction of solid waste generation using ANN	Mashhad, Iran	R = 0.86, MSE = 0.26, and MAPE = 0.046	[57]
Forecasting organic, paper, plastics, and textile waste using ANN	Johannesburg, South Africa	R-values = 0.916, 0.862, 0.834, and 0.826 for waste categories	[58]
Forecasting MSW generation quantities using ANN-PSO	Different polish cities	CE = 0.92, R = 0.96, WI = 0.98, RMSE = 11,342.74, and MBE = 6548.55	Our research study

Ali Abdoli et al. [57] employed ANN for the long-term prediction of solid waste generation in Mashhad city, Iran. Population size, household income, and maximum temperature were determined to be important determinants in solid waste output. The ANN model outperformed the multivariate regression model, with mean absolute percentage error (MAPE), MSE, and R values of 0.046, 0.26, and 0.86, respectively. Adeleke [58] employed ANN to estimate the physical waste streams in the city of Johannesburg based on meteorological factors. The input factors comprised humidity, wind speed, and maximum/minimum temperature. For forecasting organic, paper, plastics, and textile waste, optimal topologies acquired R-values of 0.916, 0.862, 0.834, and 0.826, respectively. In this study, the ANN-PSO model is associated with CE, R, WI, RMSE, and MBE metrics of 0.92, 0.96, 0.98, 11,342.74, and 6548.55, respectively. Therefore, the proposed model improves the performance metrics reported in the literature.

6. Conclusions

An accurate prediction of the municipal solid waste (MSW) generation rate is critical for sustainable and efficient MSW management. Neural network models have been recently used and proved their efficiency for modeling MSW quantities. Though previous work on waste generation prediction had been undertaken, this is the first time the optimized artificial neural network (ANN) model using particle swarm optimization (PSO) had been applied. This research applied an ANN model coupled with the PSO algorithm and conventional ANN to forecast MSW quantities in Polish cities. The performance of the models was compared using five assessment metrics, namely, coefficient of efficiency (CE), Pearson correlation coefficient (R), Willmott's index of agreement (WI), root mean squared error (RMSE), and mean bias error (MBE). To represent the effect of economic, demographic, and social factors on the rate of waste generation, selected explanatory factors were integrated into the developed models. Population, employment-to-population ratio, revenue per capita, number of entities by type of commercial activity, and number of businesses enlisted in REGON per 10,000 people were the considered criteria.

The ANN-PSO model (CE = 0.92, R = 0.96, WI = 0.98, RMSE = 11,342.74, and MBE = 6548.55) surpassed the standard ANN model (CE = 0.11, R = 0.68, WI = 0.78, RMSE = 38,571.68, and MBE = 30,652.04), according to the findings. The Wilcoxon-Mann-Whitney U-test was used to determine the significance level of the reported outputs, with a significance level of 0.05. The *p*-values for (ANN, observed) and (ANN, ANN-PSO) were all less than 0.05, indicating that the models were statistically distinct. On the contrary, the *p*-value of (ANN-PSO, observed) was more than 0.05, indicating that the difference between the models was statistically negligible. As a result, the suggested ANN-PSO model had demonstrated its efficacy in estimating MSW volumes. Furthermore, it could successfully offer the foundation for the development of modern waste management systems when used in the evaluation and forecasting of waste management demands.

As for the model limitations, each city is characterized by a different model that is dependent on its associated collected data. In addition, there needed to be records for the accumulated quantities of MSW in each city. Using statistical data in different cities, the given approach may be generalized to any city across the world. However, depending on the uniqueness of the studied country, adjusting this approach may demand matching influencing parameters. This research could be extended in the future by examining the performance of different optimization algorithms to train ANN for simulating MSW quantities. In addition, the proposed model could be further improved by applying dimensionality-reduction methods such as Principle Component Analysis (PCA) to select the most important input factors in the dataset.

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Abbreviations

AARE	Average absolute relative error
ANFIS	Adaptive neuro-fuzzy inference system
ANN	Artificial neural network
BPNN	Backpropagation neural network
CE	Coefficient of efficiency
DWT	Discrete wavelet theory
EU	European Union
GA	Genetic algorithm
MAPE	Mean absolute percentage error
MBE	Mean bias error
MENA	Middle East/North Africa
MSE	Mean squared error
MSW	Municipal solid waste
PCA	Principle component analysis
PSO	Particle swarm optimization
R	Pearson correlation coefficient
R ²	Coefficient of determination
RMSE	Root mean squared error
SVM	Support vector machine
SVR	Support vector regression
WI	Willmott's index of agreement

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