Journal of Computers Vol. 31 No. 3, 2020, pp. 216-225
doi:10.3966/199115992020063103017

Integrating SVR and ARIMA Approach to Build the Municipal Solid Waste Generation Prediction System

Yi Chen[1], Feng Dai[1*]

[1] Research Center for Mining and Metallurgy Culture and Social-economic Development in the Middle Reaches of Yangtze River, Hubei Polytechnic University, Huangshi, China
13964571@qq.com

Received 29 May 2019; Revised 5 August 2019; Accepted 6 January 2020

Abstract. With the rapid development of economy, the process of urbanization in China has become more and more rapid, and the municipal solid waste (MSW) generation also increased year by year. Considering the uncertainty and dynamic of MSW generation, the MSW generation prediction is an important prerequisite for MSW management. The SVR and ARIMA approach are integrated to build the MSW generation prediction system. The proposed model is applied to predict the MSW generation in Huangshi in the next 6 years to test the performance of the hybrid ARIMA-SVR model. The MAPE and MAPE of the hybrid ARIMA-SVR model are 5.98% and 0.64%, respectively. So, the prediction system achieves better prediction performance comparing the SVR and BPN model. The experimental results indicate that the proposed hybrid ARIMA-SVR model is a promising alternative for forecasting MSW generation. This model can not only be applied to the prediction of municipal solid waste (MSW) generation, but also can be applied for prediction in other fields.

Keywords: autoregressive integrated moving average, generation prediction, municipal solid waste, support vector regression, sustainable development

1 Introduction

With the rapid development of economy and urbanization, more and more people migrate to the cities, which causes the problem that the municipal solid waste (MSW) increases year by year. Therefore, municipal solid waste management has become an urgent problem in urban development. And the prediction of the municipal solid waste generation is critical to the sustainable development of municipal solid waste management [1].

This paper aims at establishing predictive models for enhancing MSW management by forecasting MSW generation. Generally, the MSW generation are stochastic and unplanned. It is associated with many factors, such as people's living habits, consumption pattern and resident income and so on. As a result, MSW generation forecasting is regarded as a complicated task. Above analysis highlights the need for a data-driven modeling framework that can offer accurate prediction of MSW generation.

Due to the incomplete historical data, the accurate prediction model of municipal solid waste is difficult to build [2]. Beigl et al. reviewed 45 methods for predicting municipal solid waste generation [3]. These methods can be divided into 7 categories: correlation analysis, group comparison, single regression, multiple regression, time series analysis, input-output analysis and system dynamics. In these methods, the regression analysis method is widely used in the municipal solid waste generation prediction because of its mature theory and simple algorithm [4]. However, when using incomplete data, the prediction accuracy is unsatisfied [5], and the regression analysis cannot include all the factors that affect the municipal solid waste generation [6]. Some scholars predict municipal solid waste generation using time series analysis method, and the results are more accurate than using regression model [7], especially in short-time [8-9].

---

* Corresponding Author

In recent years, artificial neural network is widely applied to predict the municipal solid waste generation, and the results is more satisfied than traditional prediction method. This method is to construct a complex nonlinear system [10-11] through a set of input and output data. However, this method needs a lot of historical data, and it has some problems such as “over learning” [12]. Based on that, some scholars make some improvement by using multi-stage chaotic model [13], Fourier series [14] and hybrid prediction model based on simulated annealing algorithm [15]. Some other scholars applied support vector machine to forecast municipal solid waste generation [16].

Stated thus, it is not difficult to find that in order to improve the prediction accuracy of municipal solid waste generation, artificial neural network algorithm is applied mostly, and also make some improvement to make up for the deficiency of artificial neural network algorithm. However, few research works focused on combining support vector machine with time series analysis to predict municipal solid waste generation, so this paper attempts to build the hybrid ARIMA-SVR model, and tests the feasibility through a case of Huangshi, a city of Hubei province in China.

2 Literature Review

2.1 Time Series Prediction Model

Time series data refers to a group of data arranging in time order. Time series analysis is to observe the time series data trend and reveal the basic structure characteristics. It is usually used to predict and control future behavior [17] and can effectively avoid the data missing of social and economic factors [18]. With dynamic feature, the time series data of MSW generation can be identified by non-linear tools. The most frequently used prediction model of time series data include moving average method, exponential smoothing method, autoregressive integrated Moving Average Model (ARIMA), etc. Among them, exponential smoothing method and ARIMA model are most widely applied in the prediction of municipal solid waste generation. The time series prediction model is perfect to predict in short-term, and if the data possesses seasonal variation characteristics, the time series prediction model can also obtain better predicted effect [19-21]. However, the time series prediction model requires historical data with higher quality. If the historical data is not smooth enough, the precise prediction can’t be obtained..

Because the MSW generation shows obvious seasonal features in different months, he ARIMA model can be applied to predict the MSW generation in the short-term [22]. However, the MSW generation prediction in long-term is not satisfied using ARIMA model.

2.2 Artificial Intelligence Algorithms in MSW Generation

Compared with the traditional prediction model, the artificial intelligent algorithm has certain advantages in the MSW generation prediction [23]. In recent years, the artificial intelligent algorithm model for the MSW generation prediction mainly focuses on the non-linear features of the historical data of MSW generation. Artificial intelligent algorithms mainly include Artificial Neural Network (ANN) and Adaptive Neural Fuzzy Inference System (ANFIS), Support Vector Machine (SVM) and so on. Artificial intelligent algorithm can effectively predict the MSW generation in long-term, medium-term and short-term.

Artificial Neural Network (ANN). Artificial neural network establishes a simple model through abstracting the human brain neuron network and forms different networks according to different connection modes. The most remarkable feature of artificial neural network prediction is its learning ability. Artificial neural network can construct a complex non-linear model through a set of input and output data. Therefore, it is widely applied in the construction of nonlinear system model [24]. The MSW generation is non-linear, which can be effectively predicted by the artificial neural network.

Ordóñez-Ponce et al. [25] predicted the long-term MSW generation rate in Chile using multi-layer perceptual neural network. They found that population, the proportion of municipal population, education level, the number of libraries and the poor people were the main factors affecting the MSW generation in Chile. So they constructed a neural network prediction model considering population, economy, geography and other factors. The model can accurately predict the MSW generation.

Noori et al. applied the artificial neural network algorithm to predict the MSW generation in short-term. They treated time series data as research data. The result shows that the feedforward neural network with one hidden layer and 16 neurons is the best model for predicting the MSW generation in short-term. However, the prediction accuracy of ANN may be affected due to the non-correlation and noise in the data. So principal component analysis, wavelet transform and gamma test are introduced to improve the prediction accuracy. Although ANN model is good at predicting MSW generation, its prediction performance is not ideal because of over-fitting and local minimization and poor generalization ability in training. [26-27]

Adaptive Neural Fuzzy Inference System (ANFIS). ANFIS is a data-driven modeling method which combines artificial neural network with fuzzy logic. Many scholars compared ANN with ANFIS on predicting MSW generation. Tiwari et al. considered three factors (economic trend, population change and garbage recycling rate) that affect the MSW generation. They believed that ANFIS is better than ANN [28] on MSW generation. Considering the incomplete data, Chen and Chain believe that ANFIS can also predict the MSW generation effectively [29]. Noori et al. [30] applied the fuzzy objective regression to improve the prediction accuracy of ANFIS on MSW generation.

Support Vector Machine (SVM). SVM is an improved neural network algorithm proposed by Vapnik et al. [31]. Based on statistical learning theory and structural risk minimization principle, SVM seeks the best compromise between model complexity and learning ability according to limited sample information. Most traditional neural network models aim to find the minimum classification error or the deviation of the positive solution of training data, while SVM searches the minimum upper bound of the overall error. The SVM is to find the global optimal solution, while other neural network models may tend to find the local optimal solution. Therefore, the SVM can effectively avoid over-fitting [32]. Abbasi et al. applied SVM model to predict weekly MSW generation in Tehran, Iran. They found that SVM had high accuracy in a short time [33]. Abbasi et al. [34] also found that dealing with input variables by wavelet transform is helpful to improve the accuracy and robustness of the prediction model.

3 Research Model

3.1 The ARIMA Model

The ARIMA model, one of time series analysis, is widely applied mostly [35]. The ARIMA model is a generalization of an autoregressive moving average (ARMA) model. Many models are fitted to time series data either to better understand the data or to predict future points in the series. ARIMA models are applied in some cases where data show evidence of non-stationarity, where an initial differencing step can be applied one or more times to eliminate the non-stationarity.

Given a time Stationary series $\{x_t\}$, the ARIMA(p, d, q) model is defined as

$$\varphi(B)\Delta^d z_t = \theta(B)a_t \tag{1}$$

where B is the backward shift operator, $\Delta = 1 - B$, which is the backward difference, d is the order of difference, $\varphi(\cdot)$ and $\theta(\cdot)$ are polynomials of order p and q, respectively.

So, ARIMA(p,d,q) model is the product of the AR(p) model part:

$$\varphi(B) = 1 - \varphi_1 B - \varphi_2 B^2 - \cdots - \varphi_p B^p \tag{2}$$

the MA(q) model part:

$$\theta(B) = 1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q \tag{3}$$

and integrating part:

$$I(d) = \Delta^{-d} \tag{4}$$

The functions $\varphi(\cdot)$ and $\theta(\cdot)$ are chosen so that the zeros of both polynomials lie outside the unit circle in order to avoid generating unbounded process.

3.2 Support Vector Regression (SVR)

Support vector regression (SVR) is simply used to describe regression with SVM. Given the training data set $D=\{(x_i, y_i)\}_{i=1}^{n}$, where $x_i \in X \subseteq R$ denotes an input vector and $y_i \in Y \subseteq R$ denotes an output vector. SVR is formulated as follows:

$$f(x,w)=\sum_{i=1}^{N} w_i \phi_i(x_i)+b \tag{5}$$

where $\phi_i(x_i)$ denotes a set of non-linear transfer function that maps the input vector into high dimensional feature space in which theoretically a simple linear regression can cope with the complex non-linear regression of the input space, and w and b denote the coefficients.

The coefficients w and b can be estimated by minimizing the following regularized risk function:

$$\frac{1}{2}\|w\|^2 + C\sum_{i=1}^{N}(\xi_i+\xi_i^*) \tag{6}$$

$$s.t.\ \ y_i - w\cdot x_i - b \le \varepsilon + \xi_i \tag{7}$$

$$w\cdot x_i + b - y_i \le \varepsilon + \xi_i^* \tag{8}$$

$$\xi_i, \xi_i^* \ge 0, i=1,2,\cdots,l \tag{9}$$

where the constant $C>0$ specifies a trade-off between an approximation error and the weight vector $\|w\|$. ε is called as the tube size that is equivalent to the approximation accuracy placed on the training data points. Both C and ε must be chosen beforehand by the user, the slack variables ξ and ξ^* represent the distance from actual values to the corresponding boundary values.

Then, the dual form of the non-linear SVR can be expressed as

$$\max W=\sum_{i=1}^{l} y_i(\alpha_i-\alpha_i^*)-\varepsilon\sum_{i=1}^{l}(\alpha_i+\alpha_i^*)-\frac{1}{2}\sum_{i=1}^{l}\sum_{j=1}^{l}(\alpha_i-\alpha_i^*)(\alpha_j-\alpha_j^*)k(x_i,x_j) \tag{10}$$

$$s.t.\ \sum_{i=1}^{l}(\alpha_i-\alpha_i^*)=0 \tag{11}$$

$$0\le \alpha_i, \alpha_i^* \le C, i=1,2,\cdots,l \tag{12}$$

where α_i and α_i^* are Lagrange multipliers. $k(x_i,x_j)=\phi(x_i)\bullet\phi(x_j)$ is a kernel function to yield the inner products in the feature space $\phi(x_i)$ and $\phi(x_j)$.

Therefore, the non-linear regression function can be given as:

$$f(x)=\sum_{i=1}^{N}(\alpha_i-\alpha_i^*)k(x_i,x_j)+b \tag{13}$$

Three hyperparameters control the quality of SVR, i.e. the error cost C, the width of the tube ε and the kernel parameter. Numbers of methods have been proposed to tune this hyperparameters vector and the basic idea of them is that: choose the hyperparameters vector that gives the best generalization performance [36].

3.3 The SVR-ARIMA Model

This study proposes a SVR-ARIMA approach for MSW generation forecasting. The ARIMA and SVR models are utilized to model the linear and nonlinear components in influencing factors (independent variable) and MSW generation (dependent variable) respectively. The flow chart of the SVR-ARIMA model is shown in Fig. 1. Firstly, the time series data including MSW generation and influencing factors is processed using normalization method, then all the data is divided into 2 group: training set and test set. Next, the kernel function is selected to train the data and optimize the parameters. After that, the SVR model is obtained. Then the test set is input into the model to test the model. When the SVR prediction model is obtained, the ARIMA model is applied to predict the influencing factors in the next stage, and the predicted factors are input into the SVR prediction model to get the MSW generation in the next stage.

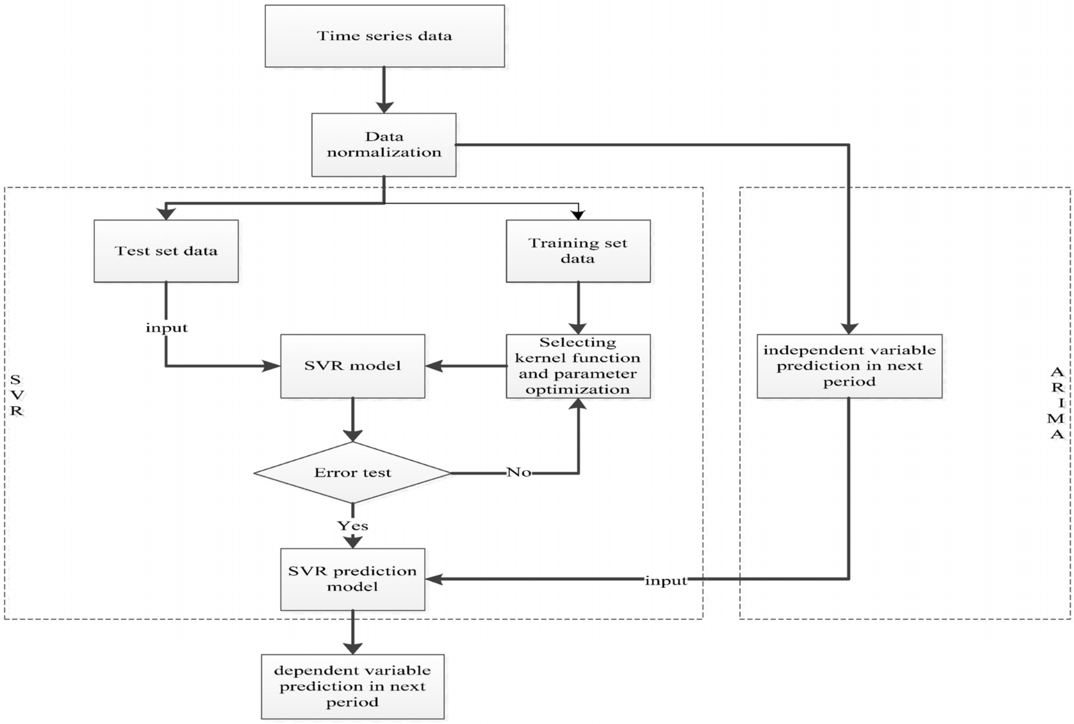

Fig. 1. The flow chart of the SVR-ARIMA model

4 Case Study

4.1 Experimental Design and Environment

How to select the influencing factors is the key to the prediction accuracy of municipal solid waste generation. There are many factors influencing the municipal solid waste generation, according to the previous researches, such as the economic level, urban residents, the annual consumption expenditure of urban residents and consumption habits, education level, the recycling awareness, climate conditions, geographical environment and relevant law and regulations and so on.

These factors can be divided into 2 groups: direct factors such as the economic level, urban residents, the annual consumption expenditure of urban residents and indirect factors such as natural factors(season, climate, geographical environment etc), individual factors(education level, consumption habits, recycling consciousness etc) and social factors(recycling education and related laws and regulations etc). In the prediction of municipal solid waste generation, it will be too complex to consider all these factors. Therefore, this paper mainly considers 3 factors: GDP, urban residents and the annual consumption expenditure of urban residents.

Usually, with the development of urban economy, the population of the city increase more and more, and the annual consumption expenditure of urban residents increases too. In this paper, Huangshi, a city of Hubei Province in China, is taken as an example to apply the SVR-ARIMA model. Therefore, the municipal solid waste generation of Huangshi will be predicted. Huangshi is located in the southeast of Hubei Province, northeast of the Yangtze River. The total area of Huangshi is 4583 square kilometers. By the end of 2017, the GDP of Huangshi was 122 billion 810 million yuan. From 1997 to 2017, the urban population increased from 819 thousand and 900 to 1 million 506 thousand and 800, and the urbanization rate reached 61.3%. The municipal solid waste generation increased from 279 thousand tons to 364 thousand tons.

4.2 Data Collection

As mentioned before, this paper mainly considers 3 influencing factors (GDP, urban residents and annual consumption expenditure of urban residents). When predicting the municipal solid waste generation, the data should be collected firstly. All the data is collected from Huangshi statistical yearbook(1998-2018) and Hubei statistical yearbook (1998-2018) (shown in Table 1).

Table 1. The data of municipal solid waste generation prediction

Year	Waste generation (thousand ton)	GDP (billion yuan)	Urban residents (thousand people)	Annual consumption expenditure of urban residents (yuan/person)
1997	27.9	86.16	81.99	3858
1998	28.4	98.19	83.53	4055
1999	29.5	122.25	84.94	4250
2000	32.3	146.32	92.67	4330
2001	27.6	170.38	108.09	4530
2002	28.2	182.41	115.8	4777
2003	28.4	208.18	116.29	4949
2004	27.7	234.52	117.23	5252
2005	27.8	259.79	117.94	5898
2006	28.3	295.91	118.39	6323
2007	28.5	328.19	119.01	6737
2008	29.6	384.9	119.87	7362
2009	31.1	447.05	121.94	8468
2010	31.2	530.57	121.95	9347
2011	31.9	571.59	122.64	10179
2012	32.5	690.12	137.98	10988
2013	33	925.96	143.52	12407
2014	34.6	1040.95	146.66	14337
2015	35.2	1142.03	147.67	14964
2016	35.9	1218.56	149.11	15459
2017	36.4	1228.1	150.68	17241

4.3 Data Pre-processing

As shown in Table 1, the dimension between variables is different. If calculating the data directly, the prediction results may be not satisfied. Therefore, in order to make the prediction data more accurate, it is necessary to normalize each variable between the [1-2]. The calculation equation is shown as follows:

$$y = 2 \times \frac{x_i - x_{\min}}{x_{\max} - x_{\min}} - 1 \tag{14}$$

18 data is applied as a training set to build SVR model, and then input all the 3 data into the SVR model to test the prediction accuracy. The libsvm toolbox developed by Professor Lin Zhiren of National Taiwan University is applied to build the SVR model and the Sequential minimal optimization (SMO) algorithm is applied to find the optimal parameter. The building model, programming and prediction are implemented by MATLAB R2016a.

Parameter optimization. When training and prediction, the kernel function must be established first. The RBF kernel function is chosen as the prediction of the municipal solid waste generation in this paper. Secondly, the penalty parameters C and RBF kernel function parameters are selected. Usually, the 2 parameters are chosen by Cross validation (CV). CV can obtain the optimal parameters and avoid the occurrence of over learning state.

Usually, there are 3 CV methods: Hold-Out Method (HOM); K-fold Cross Validation (K-CV) and Leave-One-Out Cross Validation(LOO-CV). In this paper, the K-CV method will be taken.

First, finding the optimal parameters C and σ, the mean square variance(MSE) is0.0088644, and the parameter C and σ is 0.5 and 2 respectively.

Training and regression prediction. The optimal parameters C and σ obtained above are used to train SVM model. Then, the original independent variable data is input into the model to predict the municipal solid waste generation, which are compared with the original data. The calculation result is MSE=0.0128485, R^2 =88.5%. The regression prediction result is satisfied. Therefore, this SVR prediction model is very suitable to predict the data in next stage.

4.4 Performance Evaluation and Discussion

In this section, the ARIMA model is applied to predict the independent variables of municipal solid waste generation. It is not difficult to find that the 21 data in Table 1 are equal spaced time series. In this study, the ARIMA prediction model is built based on the original data firstly, and then the ARIMA prediction model is applied to predict the 21 years' data, and compare it with the original data to observe the fitting effect and test the accuracy of prediction.

The data in Table 1 are processed by logarithmic transformation and difference operation. The ARIMA model of GDP, urban residents and annual consumption expenditure of urban residents can be fitted as ARIMA (0, 2, 0), (0, 2, 0), and (2, 2, 2) respectively.

Then, the 3 factors are predicted from 2015 to 2020 by using ARIMA model, the results is shown in Table 2.

Table 2. The predicted data of 3 factors from 2015 to 2017

Year	GDP (billion Yuan)	Urban residents (thousand people)	Annual consumption expenditure of urban residents (Yuan/person)
2015	1237.51	154.11	19369.10
2016	1246.79	157.55	20401.69
2017	1255.93	160.98	21103.77
2018	1264.95	164.42	23124.62
2019	1273.83	167.85	26198.61
2020	1282.59	171.29	28501.16

Then, the data of 3 variables in Table 2 are input into the trained SVR prediction model, and the MSW generation in Huangshi from 2015 to 2017 is obtained. The results were compared with SVR and Back Propagation Network (BPN) (shown in Table 3). The relative error (RE), MSE and MAPE are applied to measure the prediction effect. The calculation equations of MSE and MAPE are shown as follows:

$$MSE = \frac{1}{n}\sum_{t=1}^{n}(obseved_t - predicted_t)^2 \tag{15}$$

$$MAPE = \sum_{t=1}^{n}\left|\frac{observed_t - predicted_t}{observed_t}\right| \times \frac{100}{n} \tag{16}$$

Table 3. The comparison between different prediction method on MSW generation

year	Actual value	SVR-ARIMA	RE	SVR	RE	BPN	RE
2015	35.9	35.61	0.8%	35.77	0.4%	36.34	1.2%
2016	36.4	36.12	0.8%	36.41	0.03%	36.19	0.6%
2017	36.6	36.73	0.4%	37.25	1.8%	36.82	0.6%
		MSE=5.98%		MSE=14.65%		MSE=9.54%	
		MAPE=0.64%		MAPE=0.72%		MAPE=0.8%	

According to the Table 3, SVR-ARIMA model shows the minimum error on MSW generation. So, the SVR-ARIMA model is superior to predict MSW generation in the next stage. The data of 3 variables from 2018 to 2020 in Table 2 are input into the SVR-ARIMA model, the MSW generation prediction from 2018 to 2020 in Huangshi is shown in Table 4.

Table 4. The MSW generation prediction from 2018 to 2020 in Huangshi

Year	2018	2019	2020
Waste generation (10 thousand ton)	37	37.7	38.4

5 Conclusion

In this study, the hybrid SVR-ARIMA model is proposed for MSW generation prediction. The ARIMA model and the SVR model are utilized to capture the linear and nonlinear trends in influencing factors and MSW generation, respectively. Results show that, the hybrid ARIMA-SVR model is superior to single models in terms of a variety of performance criteria. Our study validates the effectiveness of proposed the hybrid ARIMA-SVR model in forecasting MSW generation.

However, only three factors are considered when constructing the hybrid ARIMA-SVR prediction model, which doesn't match the actual situation. Therefore, in future research, other factors (such as people's living habits, consumption pattern and resident income and so on) affecting the MSW generation will be taken into account.

Besides, only total MSW generation is considered, while the MSW sorting problem is ignored. Thus, the prediction for different types of MSW can be studied in the future. Moreover, feature selection is crucial for improving the performance of SVR. Therefore, more features will be incorporated in the future work.

The hybrid ARIMA-SVR model is a novel method in MSW generation forecasting. These findings are of great importance in supporting MSW management decisions, thus managing efficient MSW disposal as resource.

Acknowledgements

The study was supported by the Science and Technology Research Project of Hubei Polytechnic University (Grant No. 14xjr08Q). Research Center for Mining and Metallurgy Culture and Social-economic Development in the Middle Reaches of Yangtze River (Grant No. 2018kyy07, 2015kyb06).

Reference

[1] K.A. Kolekar, T. Hazra, S.N. Chakrabarty, A review on prediction of municipal solid waste generation models, Procedia Environmental Sciences 35(2016) 238-244.

[2] A. Maryam, A.E. Hanandeh, Forecasting municipal solid waste generation using artificial intelligence modelling approaches, Waste Management 56(2016) 13-22.

[3] B. Peter, S. Lebersorger, S. Salhofer, Modelling municipal solid waste generation: a review, Waste Management 28(1)(2008) 200-214.

[4] G. Cristina, E.N. Dragoi, E-D. Comanit, M. Gavrilescu, T. Campean, S. Curteanu, M. Gavrilescu, Forecasting municipal solid waste generation using prognostic tools and regression analysis, Journal of Environmental Management 182(2016) 80-93.

[5] V.M. Adamović, D.Z. Antanasijević, M.D. Ristić, A.A. Perić-Grujić, V.V. Pocajt, Prediction of municipal solid waste generation using artificial neural network approach enhanced by structural break analysis, Environmental Science and Pollution Research 24(1)(2017) 299-311.

[6] M. Kannangara, R. Dua, L. Ahmadi, F. Bensebaa, Modeling and prediction of regional municipal solid waste generation and diversion in Canada using machine learning approaches, Waste Management 74(2018) 3-15.

[7] M. Amon, D. Kuznetsov, S. Mirau. Time series forecasting of solid waste generation in Arusha city-Tanzania, Mathematical Theory and Modeling 4(8)(2014) 29-39.

[8] N.E Petridis, E. Stiakakis, K. Petridis, P. Dey, Estimation of computer waste quantities using forecasting techniques, Journal of Cleaner Production 112(2016) 3072-3085.

[9] K. Aistė, G. Denafas, T. Ruzgas, Forecasting hazardous waste generation using short data sets: case study of Lithuania/Pavojingųjų atliekų susidarymo prognozavimas naudojant trumpas duomenų imtis: Lietuvos atvejis, Mokslas–Lietuvos ateitis/Science–Future of Lithuania 8(4)(2016) 357-364.

[10] A. Rashi, R. Kumar, Effect of training functions of Artificial Neural Networks (ANN) on time series forecasting, International Journal of Computer Applications 109(3)(2015)14-17.

[11] K. Atul, S.R. Samadder. An empirical model for prediction of household solid waste generation rate– a case study of Dhanbad, India, Waste Management 68(2017) 3-15.

[12] M. Abbasi, M.A. Abduli, B. Omidvar, A. Baghvand, Forecasting municipal solid waste generation by hybrid support vector machine and partial least square model, International Journal of Environmental Research 7(1)(2013) 27-38.

[13] J.-W. Song, J.-Y. He. A multistep chaotic model for municipal solid waste generation prediction, Environmental Engineering Science 31(8)(2014) 461-468.

[14] D. Asante-Darko, E.S. Adabor, S.K. Amponsah. A Fourier series model for forecasting solid waste generation in the Kumasi metropolis of Ghana, WIT Transactions on Ecology and the Environment 202(2016) 173-185.

[15] J.-W. Song, J.-Y He, M.-H Zhu, D.-B Tan, Y. Zhang, S. Ye, D.-T. Shen, P.-F. Zou, Simulated annealing based hybrid forecast for improving daily municipal solid waste generation prediction, The Scientific World Journal (2014) 348-357.

[16] C.Dai, Y.-P. Li, G.-H. Huang, A two-stage support-vector-regression optimization model for municipal solid waste management–a case study of Beijing, China, Journal of Environmental Management 92(12)(2011) 3023-3037.

[17] B. Christoph, R.J. Hyndman, B. Koo, A note on the validity of cross-validation for evaluating autoregressive time series prediction, Computational Statistics & Data Analysis 120(2018) 70-83.

[18] J. Chen, G.-Q.Zeng, W.-N. Zhou, W. Du, K.-D. Lu, Wind speed forecasting using nonlinear-learning ensemble of deep learning time series prediction and extremal optimization, Energy Conversion and Management 165(2018) 681-695.

[19] A.Khosravi, L.Machado, R.O. Nunes, Time-series prediction of wind speed using machine learning algorithms: a case study Osorio wind farm, Brazil, Applied Energy 224(2018) 550-566.

[20] P. Ong, Z. Zainuddin, Optimizing wavelet neural networks using modified cuckoo search for multi-step ahead chaotic time series prediction, Applied Soft Computing 80(2019) 374-386.

[21] K. Utku, A. Arslan, Time series prediction with a hybrid system formed by artificial neural network and cognitive development optimization algorithm. Scientia Iranica, Transaction E, Industrial Engineering 26(2)(2019) 942-958.

[22] M. Fliess, J. Cédric, V. Cyril, Prediction bands for solar energy: New short-term time series forecasting techniques, Solar Energy 166(2018) 519-528.

[23] A. Khosravi, R.N.N. Koury, L. Machado, J.J.G. Pabon, Prediction of wind speed and wind direction using artificial neural network, support vector regression and adaptive neuro-fuzzy inference system, Sustainable Energy Technologies and Assessments 25(2018) 146-160.

[24] O. Verónica, V. Sousa, C. Dias-Ferreira, Artificial neural network modelling of the amount of separately-collected household packaging waste, Journal of Cleaner Production 210(2019) 401-409.

[25] O.P, Eduardo, S. Samarasinghe, L. Torgerson, Artificial neural networks for assessing waste generation factors and forecasting waste generation: a case study of Chile, Journal of Solid Waste Technology and Management 32(3)(2006) 167-184.

[26] R.E. Nouri, M.A. Abdoli, A. Farokhnia, A. Ghaemi, Solid waste generation predicting by hybrid of artificial neural network and wavelet transform. Journal of Environmental Studies 35(49)(2009) 25-30.

[27] R.E. Nouri, M.A. Abdoli, M.J. Ghazizade, R. Samieifard, Comparison of neural network and principal component-regression analysis to predict the solid waste generation in Tehran, Iranian Journal of Public Health (2009) 74-84.

[28] T.M. Kumar, S. Bajpai, U.K. Dewangan, Prediction of industrial solid waste with ANFIS model and its comparison with ANN model-A case study of Durg-Bhilai twin city India, International Journal of Engineering and Innovative Technology (IJEIT) 6(2)(2012) 192-201.

[29] H.-W. Chen, N.-B. Chang, Prediction analysis of solid waste generation based on grey fuzzy dynamic modeling, Resources, Conservation and Recycling 29(1-2)(2000) 1-18.

[30] R.E. Nouri, M.A. Abdoli, A. Farokhnia, M. Abbasi, RETRACTED: Results uncertainty of solid waste generation forecasting by hybrid of wavelet transform-ANFIS and wavelet transform-neural network, Expert Systems with Applications (2009) 9991-9999.

[31] V. Vladimir, The Nature of Statistical Learning Theory, Springer Science & Business Media, 2013(Chapter 4).

[32] K.-J. Kim, Financial time series forecasting using support vector machines, Neurocomputing 55(1-2)(2003) 307-319.

[33] M. Abbasi, M.A. Abduli, B. Omidvar, A. Baghvand, Forecasting municipal solid waste generation by hybrid support vector machine and partial least square model, International Journal of Environmental Research 7(1)(2013) 27-38.

[34] M. Abbasi, M.A. Abduli, B. Omidvar, A. Baghvand, Results uncertainty of support vector machine and hybrid of wavelet transform-support vector machine models for solid waste generation forecasting, Environmental Progress & Sustainable Energy 33(1)(2014) 220-228.

[35] H. Liu, H.-Q. Tian, Y.-F. Li. An EMD-recursive ARIMA method to predict wind speed for railway strong wind warning system, Journal of Wind Engineering and Industrial Aerodynamics 141(2015) 27-38.

[36] F. Zhang, C. Deb, S.-E. Lee, J. Yang, K.W. Shah Time series forecasting for building energy consumption using weighted Support Vector Regression with differential evolution optimization technique, Energy and Buildings 126(2016) 94-103.