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Coastal solid waste prediction by applying machine learning approaches (Case study: Noor, Mazandaran Province, Iran)

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ABSTRACT
Nowadays, intelligent systems are used as innovative tools in different environmental issues. However, the prediction of short-term waste, unlike the long-term scale, is less developed due to more uncertainties and the difficulty in determining measurable independent parameters. In this study, two types of artificial neural networks (MLP and RBF) and two decision tree algorithms (CHAID and CART) have been used as effective tools for short-term forecasting of total waste production in coastal areas of Noor in Mazandaran Province, Iran. So that, average temperature, daily rainfall, sunny hours, maximum relative humidity and maximum wind speed were determined as the most important independent parameters, while the amount of waste produced in the coastal areas of Noor was considered as the dependent variable. Wastes from the coastal areas were gathered and their weights were analysed during 12 months from July 2017 through June 2018. Samplings were carried out twice a week, three weeks of a month and 12 months of a year, overall 72 times a year. The required meteorological data was gathered from the meteorological station in Noor. Then the sensitivity analysis was performed to check the independency of the major independent parameters. Thereafter, the mentioned machine learning approaches were applied to predict the short-term total waste production in IBM SPSS Modeler version 18 environment. In the applied models, 60% of data were used in training the model and the other 40% were used for model evaluation. The results indicated that the CHAID tree algorithm exhibits a better performance in predicting total solid waste production compared to CART, MLP and RBF models. The mean absolute error and the correlation coefficient (R) of CHAID algorithm was 0.067 and 0.828, respectively.

Keywords: Solid waste, neural network, decision tree, prediction.

INTRODUCTION
One of the most important environmental problems in coastal areas of Iran is the lack of proper waste management. A large amount of waste is accumulated in the coastline every day, causing serious damage to the environment (Jozi *et al.* 2012; Abdoli *et al*. 2015). Therefore, in order to improve the environmental and sanitary aspects of the coasts, planning and proper management of produced solid waste is necessary. So that, one of the most important factors is the precise knowledge in predicting the solid waste production, which, due to the high uncertainty and the various influencing parameters, is one of the most difficult tasks in waste management. Forecasting the amount of waste produced, is the most important step in planning, determining the volume of investment for machineries, the size of storage containers in place, transmission stations and the capacity of processing, recycling and disposal sites (Hyun Il *et al.* 2011; Abbasi *et al*. 2012). In the past decade, many studies have been conducted to predict

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the amount of solid waste, most important of those included traditional methods such as material balance analysis, load counting analysis and new approaches such as multivariate linear regression (Ghazi Zade & Noori 2008; Noori *et al*. 2009). Recently, the development of intelligent systems such as neural networks helped the researchers in predicting the rate of solid waste production (Nasrollahi- Sarvaghaji *et al*. 2016). For example, Shamshiry *et al*. (2014) used a comparison of artificial neural networks (ANN) and multiple regression analysis (MRA) to predict the amount of solid waste production in the tourism area of Langkawi Island. They concluded that, in terms of prediction accuracy, artificial neural network is more accurate than regression analysis.

Sodanil & Chatthong (2014) used an artificial neural network to predict the amount of waste produced in Bangkok, reporting that the three-layer network structure with 3-35-1 neuron had the best performance. Patel *et al.* (2013) used ANN to predict municipal solid waste production in Gujarat, India, suggesting the ANN model to predict solid waste generation for 25 years and concluding that its performance is satisfactory. Shahabi *et al*. (2012) provided a suitable model for predicting the weight of waste production in Saqqez city, Iran by an artificial neural network approach. Ghazi Zade & Noori (2008) also suggested an appropriate model for predicting the production of municipal solid wastes in Mashhad, Iran using artificial neural network concluding that the ANN model has more advantages than traditional methods in predicting the production of urban solid wastes. Besides, Abdoli *et al.* (2007) used the artificial neural network and multivariate statistical methods to predict the production of solid waste in Tehran city. Their results exhibited the absolute superiority of the ANN model compared to the hybrid regression and principle component analysis (PCA).

Mohanbaba *et al.* (2012) determined the suitable soil type in the land filling of electronic wastes by applying decision tree algorithms. Their results indicated that clay soils are the best option for this goal. Johnson *et al.* (2017), using decision tree algorithm, predicted the mass of weekly waste production in 232 locations in New York City with high precision. The average accuracy of their model was 88% which was dominantly due to its fine spatial and temporal waste data. Kontokosta *et al*. (2018), using the neural network and decision tree algorithm, predicted the amount of daily and weekly production of solid waste in buildings with an acceptable accuracy. They use R-square and RMSE as the statistical parameters to evaluate the applied model. Their results indicated that the R-square and RMSE for NN and also for the decision tree algorithms were 0.77, 0,05 and 0.87, 0.034, respectively. Minousepehr *et al*. (2018) predicted the rate of waste production per capita in coastal areas of Hormozgan Province, Iran, using decision tree (M5P model), support vector machines (SVM) and artificial neural network algorithms (MLP model). They used 75% and 25% of data in training and model validation processes. The RMSE and mean absolute error (MAE) were also used as validation parameters. Their results revealed that the predictive error of the decision tree approach was lower than the other two methods. Hence, in the present study, because of the importance of short-term prediction of produced waste in the coastal areas, we conducted this research to predict total daily solid waste in Noor, Mazandaran Province, Iran.

MATERIALS AND METHODS

Study area and data gathering

Noor, a city with a population of 26947, is located at 36° 34’ 25” N and 52° 00’ 50” E. The length of the city coastline is about 11 km (Fig.1.a). Based on the existing maps of the city coastline, site visit results and due to the integrity of the beach, as well as convenient access, three monitoring stations were selected purposefully to sample produced wastes in this study (Fig.1.b). Wastes from the coastal areas of Noor city were gathered and analysed during a period of 12 months from July 2017 to May 2018. Sampling was carried out twice a week (in order to investigate the effects of tourism and holidays on waste, samples were taken on Mondays and Thursdays), three weeks of a month, 12 months of a year and overall 72 times a year. A total of 216 samples were obtained from three sites. After weight analysis, total amount of produced waste was obtained. The meteorological data were taken from the meteorological station of Noor city followed by extracting information of the sampling days from these data.

Factors such as temperature, humidity and rainfall are factors affecting the amount of waste produced. So that, in this study, daily average temperature, sunny hours, daily rainfall, maximum relative humidity and maximum wind speed were selected as the most effective independent parameters in estimating the total amount of waste produced and used as input data of models. We examined the ability of ANN models and decision trees to predict the total amount of solid waste. Further data analysis was performed using IBM SPSS Modeler ver.18.

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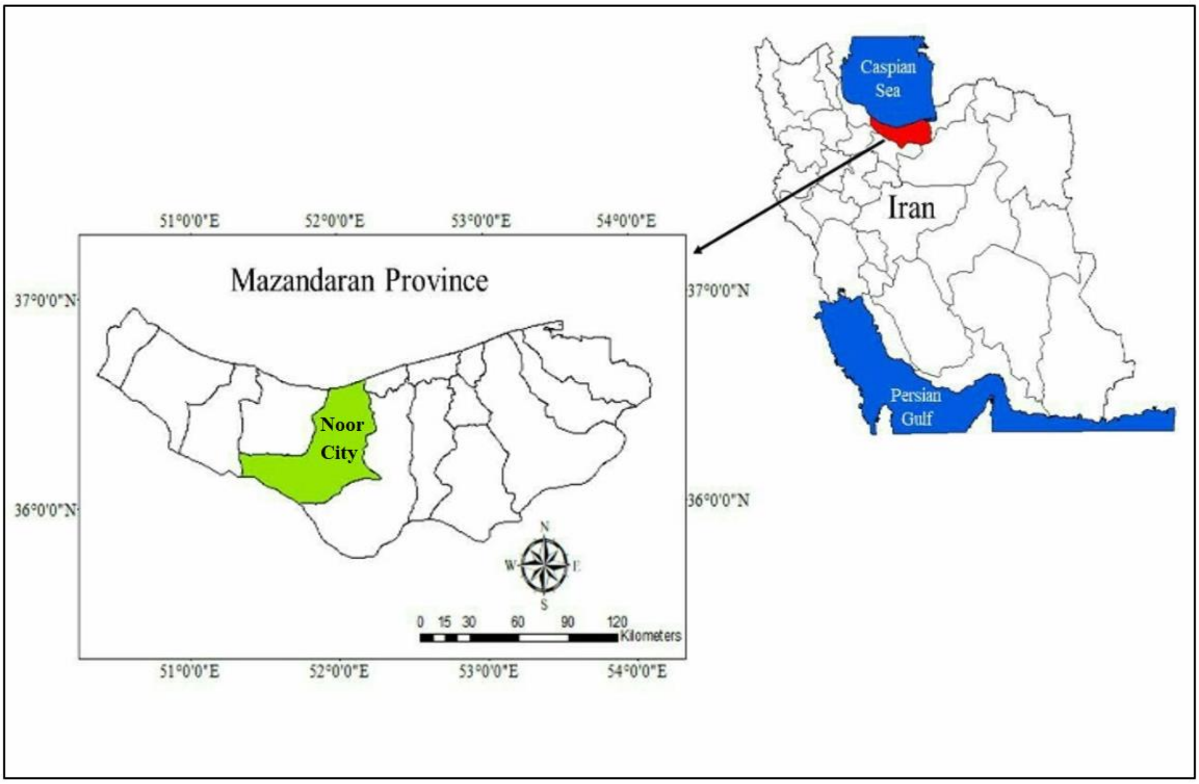

(a)

(b)

Fig. 1. The location of a) study area and b) data gathering sites at the coastal line of Noor, Mazandaran Province, Iran.

Machine learning approaches

In this study, the ability of multi-layer perceptron (MLP) and radial basis function (RBF) as two types of artificial neural network methods and Chi-squared automatic interaction detector (CHAID) as well as classification and

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regression trees (CART) as two decision tree algorithms were employed to predict total waste production in northern coastal areas of Mazandaran Province.

Artificial neural network (ANN)

An artificial neural network is a cellular information processing system based on the structure of the human brain and its nervous system, in which neurons deal with problems or store information through their interconnections (Cay *et al*. 2012; 2013). As a rule, in neural networks, all available data is divided into two sets of training and testing. The training set is used by the learning algorithm to calculate network weights and the test set is used to evaluate the predicted accuracy of the trained network. Generally, the neural network consists of three layers of input, one or more hidden layers and an output layer. Neurons send raw data from the input layer to the hidden one, and then send from the hidden layer to the output one. In other words, the outputs are obtained through the processing of raw data in the input and hidden layers using weights, activation functions, biases (thresholds), aggregation functions and learning approaches. Weights are values that increase or decrease the strength of a signal. The activation function creates a linear or nonlinear relationship between input and output signals of a neuron. Selection of an appropriate activation function is very important in the performance of a neural network. Generally, there are many types of activation functions used to process the neuron outputs in the neural network. In this study, a logarithmic sigmoid activation function has been used (Fig. 2).

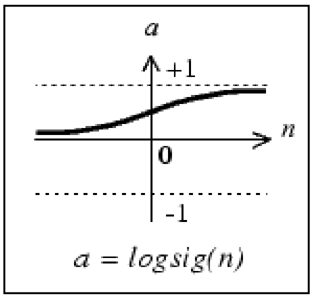

Fig. 2. Logarithmic sigmoidal function.

The activation function of the logarithmic sigmoid function illustrated in Fig. 2, is as follow:

$$a = f(n) = \frac{1}{1+e^{-n}} \quad \textbf{(1)}$$

in which, n is the input signal and a is the output one which is limited between zero and unity. To use the data as input signals of the activation functions, they should be normalized using Eq. 2.

$$X_{n}= \frac{X - X_{min}}{X_{max} - X_{min}} \quad \textbf{(2)}$$

where, X_n, X, X_{min} and X_{max} are the normalized variable, input variable, the minimum and the maximum value of input variable, respectively.

Multilayer perceptron (MLP)

The most common pattern of artificial neural networks is multilayer perceptron, which is most widely used among different models of neural network. The MLP neural network is a fully connected feedforward neural network in which every node in a layer connects to all nodes in the next layer with a specific weight. This type of network uses a supervised training algorithm in which the output is compared with the desired output and the error is obtained to modify the network weights (Kalogirou 2003).

Radial basis function (RBF)

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A radial basis network is a feedforward network. Unlike the MLP network that gives an equal importance to all input variables, each hidden neuron in a RBF network has a larger output when the network input vector is closer to the centre of the nonlinear activation function of the neuron. By increasing the Euclidean distance of the input vector from the centre of the function, the output of the neuron decreases.

Decision tree approach

Decision tree algorithm is based on a tree hierarchy structure, where, at each stage, the decision making is transferred into a specific branch or leaf of the tree. In other words, the decision tree can be considered as a multiple conditional statement in a programming language, except that in the decision tree structure, the machine optimizes the number of conditions. The decision tree method, like artificial intelligence, is one of machine learning algorithms (Zarkami *et al.* 2010; Kannangara *et al.* 2018). The major difference between the decision tree and the ANN is that in the neural networks only the predicted value is visible, but the way of decision and prediction is in a black box (hidden layers). However, in the decision tree, condition statements in all branches are visible. In addition, unlike the neural network, it is possible to study qualitative and non-numerical data in the decision tree structure (Hand *et al.* 2001; Omidvar *et al.* 2014). The decision tree can be used for the purpose of regressing continuous data or the classification of discrete data (Breiman *et al*. 1984; Hand *et al.* 2001; Alimohamadi *et al*. 2014). The decision tree is used in different fields for prediction or classification. Recently, the application of decision tree techniques has become widespread in predicting the amount of waste and especially for long-term waste prediction. In this study two decision algorithms including CHAID (Kass 1980) and CART (Breiman *et al*. 1984) have been used, which both of them can be applied for regression purposes.

CART algorithm

This algorithm has a binary structure in which the root node or parent is split into two leaves or child, and then each branch is split into two branches in turn, until no further gain can be achieved by the tree or other pre-defined criteria stop the splitting. This algorithm creates a series of optimal pruned trees. Choosing the optimal tree is performed by evaluating the performance of each pruned tree for the independent input data set (Alimohamadi *et al.* 2014; Panahi & Mirhashemi 2015).

CHAID algorithm

Unlike the CART method, this algorithm does not have a binary structure, because at each node, parents can be divided into more than two children or nodes. This algorithm uses the Chi-Square test for discrete data and the F-test for continuous data. In general, in the mentioned algorithms, the parameter or index that is in the higher level of the decision tree, has a greater impact on the dependent variable.

Validation criteria

To evaluate the performance of ANNs and decision trees, two statistical indices R (correlation coefficient) and mean absolute error (MAE) were used accordance to Equations 3 and 4.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(W_{Oi}-W_{Pi})^2}{\sum_{i=1}^{n}(W_{Oi}-\overline{W_O})^2} \qquad \textbf{(3)}$$

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|W_{Oi} - W_{Pi}| \qquad \textbf{(4)}$$

where, W_{Oi}, W_{Pi} and $\overline{W_O}$ are observed value, predicted value and mean of observed data set, respectively.

RESULTS

Total daily solid waste prediction

The sensitivity analysis results showed that among the independent parameters, daily average temperature, sunny hours, maximum relative humidity, daily rainfall and maximum wind speed were the most effective independent parameters on the daily solid waste production. In all applied models, 60% of data were used for training the model and the other 40% for evaluating the model. In this section, the results of ANNs and decision trees methods are presented. Statistical analysis of ANN models exhibited that the MLP model, constructed with 2 neurons in a

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hidden layer, has a correlation factor R = 0.642 and MAE = 0.106 for the test data. The topological structure of the MLP model is illustrated in Fig. 3. Regarding the functional differences of MLP neural network with RBF, the RBF model with 9 neurons in a hidden layer was used to predict the total daily solid waste production. The correlation coefficient and mean absolute error of the RBF network for the test data were 0.620 and 0.105, respectively. Fig. 4 displays the most important independent parameters used in the MLP algorithm.
According to Fig. 4, the most important input factors are average temperature, maximum wind speed, maximum relative humidity, sunny hours, and daily rainfall. It also illustrates that the average temperature is the most effective parameter on solid waste production in coastline of Noor city based on the MLP prediction results.

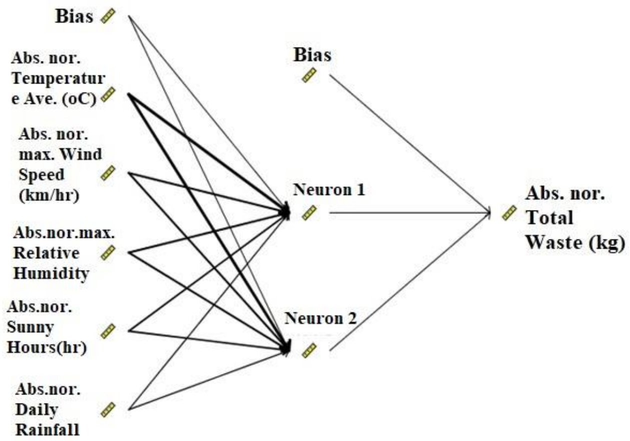

Fig. 3. Topological structure of the MLP approach in predicting the daily solid waste.

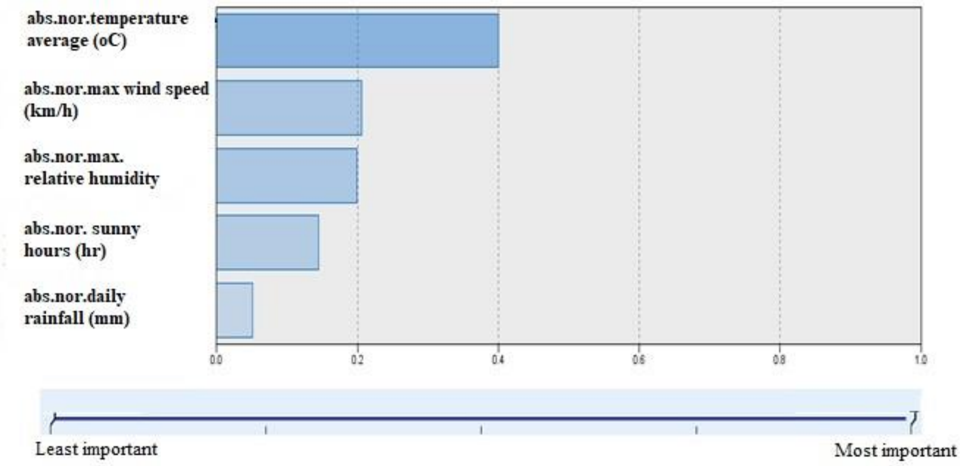

Fig. 4. Relative importance of the independent variables in MLP method.

The mentioned statistical parameters are also computed for the results of decision tree algorithms. The statistical parameters of CHAID and CART decision tree algorithms along with the statistical parameters of ANN approaches are presented in Table 1. According to this Table, the performance of two ANN models in predicting the amount of produced solid waste is approximately the same, although the performance of MLP method is slightly better. Besides, the CHAID model has a better performance than the CART model in predicting total waste production. In the overall comparison, the CHAID decision tree model exhibited better performance than the MLP, RBF and CART models. In comparison, the results of the present work agreed well with the results of Kontokosta *et al*. (2018) and Minousepehr *et al.* (2018), in which, the prediction accuracy of decision tree method was higher than NN approaches. Furthermore, according to Figs. 4 and 5, the most affecting parameters on the

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solid waste production forecasting are meteorological parameters such as average temperature and sunny hours. This finding is also consistent with the results of Kontokosta *et al*. (2018). The hierarchical structure of the CHAID model is depicted in Fig. 5. As shown in this Fig., the CHAID algorithm in the first branch of the tree diagram uses sunny hours, indicating that in this algorithm, the most effective parameter in predicting the total solid waste is sunny hours. Thereafter, sunny hours are divided into seven branches, each is attached to several leaves.
Based on the values of sunny hours, the second most important independent parameter may be wind speed, relative humidity or the daily average temperature parameter. Each branch of the tree finally ends to a specific terminal leaf or node. In the CHAID tree shown in Fig. 5, there are 53 leaves. In each route of the decision tree, the terminal node or leaf which represents the predicted value of solid waste, is not illustrated in this Fig.

Table 1. Evaluation results of the applied predicting approaches.

Parameter / Algorithm	Training		Validation		Testing	
	MAE	**R**	**MAE**	**R**	**MAE**	**R**
MLP	0.112	0.518	0.099	0.442	0.106	0.642
RBF	0.113	0.513	0.103	0.365	0.105	0.620
CHAID	0.064	0.852	0.046	0.909	0.067	0.828
CART	0.081	0.776	0.093	0.51	0.091	0.651

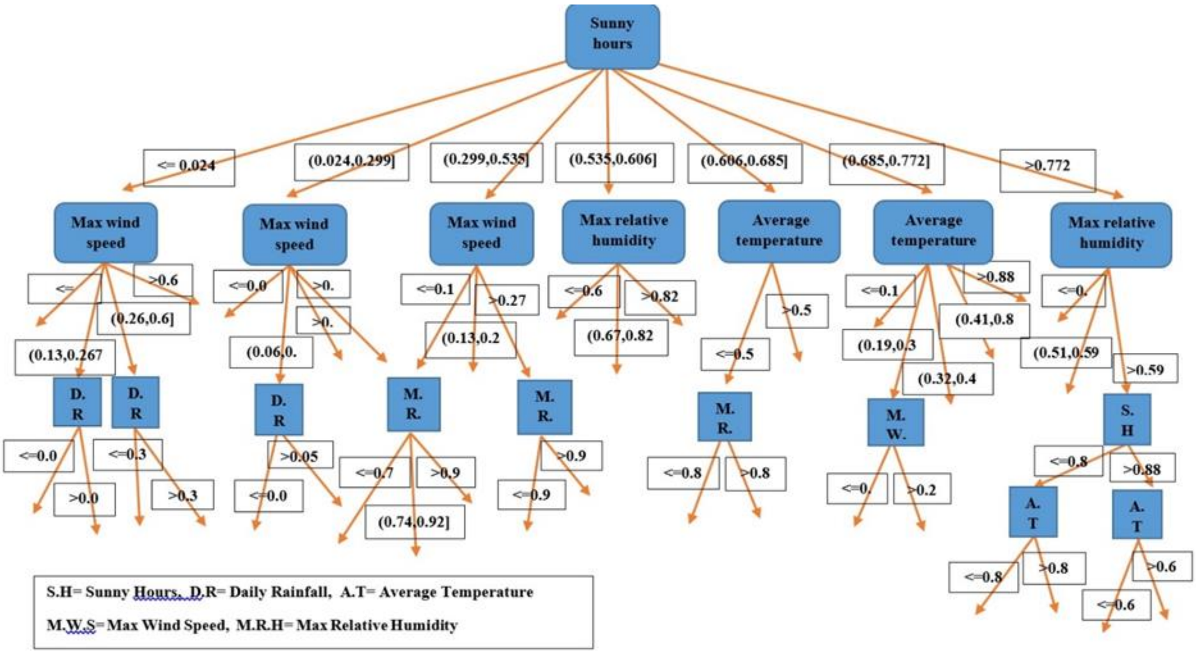

Fig. 5. Hierarchical decision algorithm of CHAID method.

CONCLUTION

Application of data mining techniques, including decision tree models, so far, can be a good substitute to the methods applied for prediction of the amount of solid waste. The results of this study indicated that the CHAID tree model has a better performance in predicting total daily waste production compared to the CART as well as artificial neural network models. Also, among the affecting independent parameters, the sunny hour parameter is the most important parameter influences the total solid waste. The most prominent features of decision tree models in comparison with other predicting models are their high prediction accuracy, ease in interpreting the results, and their nonlinear structure. As a result, this method may be useful to predict short-term solid waste production, especially in areas with non-approved measured data due to inadequate budget and limited measuring equipment. Notably, in spite of the long-term prediction of solid waste, in short-term prediction, the independent parameters should also have a short-term impact. Therefore, determining these parameters and measuring them is one of the shortcomings in short-term solid waste prediction research area.

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پیش‌بینی پسماند جامد مناطق ساحلی با استفاده از روش‌های یادگیری ماشین

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چکیده

امروزه سازگان‌های هوشمند در زمینه‌های مختلف محیط زیست به عنوان یک ابزار نوظهور استفاده می‌شوند. پیش‌بینی مقدار پسماند در مقیاس کوتاه مدت برخلاف مقیاس بلند مدت و به دلیل عدم قطعیت بیشتر و دشواری در تعیین فراسنجه‌های مستقل قابل اندازه‌گیری، کمتر توسعه یافته است. در این پژوهش دو نوع شبکه عصبی مصنوعی (MLP و RBF) و دو الگوریتم درخت تصمیم‌گیر (CHAID و CART) به عنوان ابزار مناسب برای پیش‌بینی کوتاه مدت کل پسماند تولیدی در مناطق ساحلی شهر نور در استان مازندران استفاده شد. برای این منظور دمای متوسط، بارندگی روزانه، ساعات آفتابی، بیشینه رطوبت نسبی و بیشینه سرعت باد به عنوان مؤثرترین فراسنجه‌های مستقل شناخته شدند و مقدار کل پسماند تولیدی در نواحی ساحلی شهر نور به عنوان فراسنجه وابسته در نظر گرفته شد. زباله‌های تولیدی در یک دوره دوازده ماهه از تیر ۱۳۹۶ تا خرداد ۱۳۹۷ جمع‌آوری و وزن آنها اندازه‌گیری شد. نمونه‌برداری دو بار در هر هفته، سه هفته در هر ماه و دوازده ماه در طول سال انجام شد و جمعا ۷۲ نمونه در سال برداشت شد. داده‌های هواشناسی نیز از ایستگاه هواشناسی شهر نور دریافت شد. سپس به منظور بررسی عدم وابستگی فراسنجه‌های مستقل، آنالیز حساسیت انجام شد. پس از آن از الگوریتم‌های یادگیری ماشین مذکور برای پیش‌بینی مقدار پسماند تولیدی در نرم افزار IBM SPSS نسخه ۱۸ استفاده شد. ۶۰ ٪ داده‌ها برای آموزش مدل‌ها و ۴۰٪ باقیمانده نیز برای صحت سنجی مدل‌ها استفاده شدند. نتایج نشان داد که الگوریتم CHAID نسبت به روش‌های CART، MLP و RBF عملکرد بهتری در پیش‌بینی کل پسماند دارد. میانگین خطای مطلق و ضریب همبستگی (R) برای الگوریتم CHAID به ترتیب برابر با ۰/۰۶۷ و ۰/۸۲۸ بود.

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