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Predicting air pollutant emissions from a medical incinerator using grey model and neural network

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ABSTRACT

This paper represents the first study to use the grey model (GM) for predicting CO_2, SO_2 and O_2 in the emissions from a medical incinerator. The artificial neural network (ANN) was also employed for comparison. Four control parameters were served as the input variables. The results indicated that two control parameters of temperature highly influenced air pollutant emissions. The minimum mean absolute percentage errors of 3.70%, 6.11% and 1.08% for CO_2, SO_2 and O_2 could be achieved using GMs, meanwhile the minimum root mean squared errors for three air pollutant were 0.1660, 2.4521 and 0.2112. The control parameters could be applied to the prediction of air pollutant emissions. It also revealed that GM could predict the air pollutant emissions even though emission data were not sufficient.

1. Introduction

Treatment and disposal of waste become more important in Taiwan because the amount of waste generated from households, business and industries is steadily increasing every year with the expansion of population. The more acceptable waste disposal process in the past decades was landfill, but this process encountered serious challenge because the available cites for landfill became less and less. To overcome the difficulties, the Environmental Protection Administration (EPA) of Taiwan has adopted a strategy in which incineration is adopted as the primary method of treatment and landfill as a supplement. Among the waste, medical waste is defined as hazardous waste and strict treatment and disposal is required. If incineration is adopted for treatment of medical waste, the air pollutant emissions must meet the Waste Incinerator Air Pollutant Emissions Standards (WIAPES). In order to save cost, the investigation of air pollutant emissions from incinerator is only carried out to meet WIAPES, so their investigation data are few and incomplete compared with general study cases. Under this situation, the air pollutant emissions cannot be predicted appropriately using some numerical models, especially mechanism models. Some soft computation techniques, such as artificial neural network (ANN), in which the mechanism reactions can be ignored are available presently and applied in prediction of air pollutant emissions. Although ANN can predict the air pollutant emissions from incinerators successfully, many data are required for further calculation [1–5].

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Due to the fact that only few parameters are selected for regulation in WIAPES, it is necessary to adopt a suitable method to present these limited data appropriately. In order to gain consistent results from the investigation data and predict the air pollutant emissions, the grey system theory (GST) is a suitable method.

The GST proposed by Deng [6,7] can resolve the problem of incomplete data and has been applied in our previous works [8–16]. GST focuses on the relational analysis, model establishment, and prediction of the indefinite and incomplete information. It requires only a small amount of data and the better prediction results can be obtained.

There are many analysis methods in GST including grey model (GM). GM can be used to establish the relationship between many sequences of data and its coefficients can be used to evaluate which sequence of data influences system extraordinarily.

GM was adopted for forecasting the effluent quality from different wastewater treatment plant and good results were obtained in our previous study [9]. However, the incinerator temperature not only affects the air pollutant species but also affects the concentrations due to the expansion or shrinkage of air volume. The air pollutant emissions are more complicated. Therefore the better operation strategy of medical incinerator could be found out if the relation between the control parameters and air pollutant emissions can be established.

The objectives of this study are listed as follows. (1) Employ GM to determine the control parameters of a medical incinerator which highly influenced air pollutant emissions. (2) Utilize GM to establish the emitted CO_2, SO_2 and O_2 characteristics, subsequently to forecast the air pollutant emissions. (3) Furthermore, a comparison between the proposed GM model and traditional ANN was also made to evaluate the performance.

2. Materials and methods

2.1. Treatment process

The medical incinerator located in middle of Taiwan was selected for study. The type of this medical incinerator was fixed bed and batch feeding was adopted. Its maximum designed handling capacity (MDHC, maximum weight of waste fed into the incinerator per batch) and maximum designed feeding rate (MDFR, maximum designed handling capacity divided by batch time) was 9 tons per day and 375 kg hr^{-1}, respectively. The MDHC and MDFR was fixed value and determined in accordance with incinerator function and mass balance. Although MDHC and MDFR was fixed values, the handling capacity (HC, weight of waste fed into the incinerator per batch) and feeding rate (FR, handling capacity divided by batch time) varied with daily hauling amount of medical waste and operation time. Both HC and FR reflected the operation and performance of the medical incinerator. Therefore, the control parameters including HC, FR, temperature of first stage ($Temp_1$) and temperature of second stage ($Temp_2$) were used as the input variables. The output variables included effluent CO_2, SO_2 and O_2. These compounds were continuously monitored using a gas analyzer (SIEMENS, ULTRAMAT 23). The control parameters and air pollutant emission data in one day were recorded and investigated. They were sampled and investigated every 5 min and their total number was 78. Among the total number of data, the number for training and testing (predicting) was 68 and 10, respectively.

2.2. Grey modeling process

When system information is not sufficient, GM can be created to describe the behavior of the few outputs using fewer (at least 4) system information. Through accumulated generating operation (AGO), the disorderly data may be converted into exponentially orderly form such that the system behavior can be characterized using a first-order differential equation. Solving the differential equation may yield a time relative solution for prediction. By means of inverse accumulated generating operation (IAGO), the prediction can be transformed back to the sequence of original series. A grey modeling process is described as follows.

Assume that the original series of data with n samples is expressed as: $X^{\{0\}} = (x^{(0)}(1), x^{(0)}(2), \ldots, x^{(0)}(n))$, where the superscription (0) of $X^{(0)}$ represents the original series. Let $X^{(1)}$ be the first-order AGO of $X^{(0)}$, whose elements are generated from $X^{(0)}$: $X^{(1)} = (x^{(1)}(1), x^{(1)}(2), \ldots, x^{(1)}(n))$, where $x^{(1)}(k) = \sum_{i=1}^{k} x^{(0)}(i)$, for $k = 1, 2, \ldots, n$. Further operation of AGO can be conducted to derive the r-order AGO series, $X^{(r)}$: $X^{\{r\}} = (x^{(r)}(1), x^{(r)}(2), \ldots, x^{(r)}(n))$, where $x^{(r)}(k) = \sum_{i=1}^{k} x^{(r-1)}(i)$, for $k = 1, 2, \ldots, n$. The IAGO is the inverse operation of AGO. It converts the AGO-operational series back to the one lower order form. The operation of IAGO for the first-order series is described as follows: $x^{(0)}(1) = x^{(1)}(1)$ and $x^{(0)}(k) = x^{(1)}(k) - x^{(1)}(k-1)$ for $k = 2, 3, \ldots, n$. Extending this representation to the IAGO of r-order series, the following form can be obtained, $x^{(r-1)}(k) = x^{r}(k) - x^{r}(k-1)$ for $k = 2, 3, \ldots, n$. The tendency of AGO can be approximated by an exponential function. Its dynamic behavior is analogous to a form of differential equation. Therefore grey model GM (h, N) adopts an n-order differential equation to fit the AGO-operational series. The parameters h and N in GM (h,N) denotes the order and the number of variables in the relative differential equation, respectively. The GM (h,N) can be generally expressed as

$$\sum_{i=0}^{h} a_i \frac{d^{(i)} x_1^{(1)}}{dt^{(i)}} = \sum_{j=2}^{N} b_j x_j^{(1)}(k), \tag{1}$$