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Research Article

A Multivariate Grey Prediction Model Using Neural Networks with Application to Carbon Dioxide Emissions Forecasting

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The forecast of carbon dioxide (CO_2) emissions has played a significant role in drawing up energy development policies for individual countries. Since data about CO_2 emissions are often limited and do not conform to the usual statistical assumptions, this study attempts to develop a novel multivariate grey prediction model (MGPM) for CO_2 emissions. Compared with other MGPMs, the proposed model has several distinctive features. First, both feature selection and residual modification are considered to improve prediction accuracy. For the former, grey relational analysis is used to filter out the irrelevant features that have weaker relevance with CO_2 emissions. For the latter, predicted values obtained from the proposed MGPM are further adjusted by establishing a neural-network-based residual model. Prediction accuracies of the proposed MGPM were verified using real CO_2 emission cases. Experimental results demonstrated that the proposed MGPM performed well compared with other MGPMs considered.

1. Introduction

Carbon dioxide (CO_2) is mainly produced from fossil fuel combustion [1], and reducing the impact that energy consumption and economic growth have on CO_2 emissions has become a global challenge [2]. According to the International Energy Agency (IEA) [3], total emissions of greenhouse gas in 2018 were a record 33.1 billion tons, along with a global economic growth rate that increased by 3.2%. Despite a CO_2 emission plateau from 2014 to 2016, the IEA reported that China and USA were the highest energy-using and carbon-emitting countries, and CO_2 emissions went up in each country by 2.5% and 3.1%, respectively, mainly arising from an increased use of fossil fuel to meet the energy demand. In fact, CO_2 emissions can significantly give rise to climate change and have a negative impact on economic growth. Therefore, to keep a green economic growth, the national authorities make an effort to devise energy development policies that reduce the impact of CO_2 emissions. An accurate forecast of CO_2 emissions becomes a remarkable issue when public sectors set up policies.

From the viewpoint of the grey system theory [4–6], the prediction of CO_2 emissions can be viewed as a grey system problem because although the relevant features, such as energy consumption, population, and gross domestic product (GDP) [7–9], influence CO_2 emissions, the precise relationship between these features and emissions is not clear. Furthermore, it is possible that emissions data do not conform to any statistical assumptions [7]. Compared with the prediction models implemented by artificial intelligence techniques [10–15], statistical models including logistic models [16], multivariate regression [17, 18], and time series analysis [19, 20], MGPMs have the advantage of characterizing an unknown system using limited samples [6], without requiring conformance with statistical assumptions. Despite huge amount of data we can collect, only a few sample data points are required to achieve reliable and acceptable prediction accuracy [21, 22]. Therefore, it is interesting to apply the multivariate grey prediction models (MGPMs) to CO_2 emissions.

In contrast to the frequently used GM (1, 1), the first-order grey differential equation with one variable, which does not consider the influence of relevant factors on the system [23], the GM (1, *N*), which consists of a system's characteristic sequence and several relevant factor sequences, is fundamental to MGPMs and has been widely applied to time series forecasting, such as the forecasting of traffic flow [24], number of motor vehicles [25], production in high-tech industries [26, 27], energy consumption [28, 29], integrated circuit output [30, 31], OFDI analysis [32], and pattern classification [33, 34]. Many GM (1, *N*) variants have been introduced to improve the prediction accuracy of the traditional GM (1, *N*), such as a rolling multivariable model [8], background value optimization [27], the optimization of GM (1, *N*) (OGM (1, *N*)) using grey differential equations with linear correction and grey quantity terms [25, 35], nonlinear grey models (NGM (1, *N*)) using grey differential equations with power exponents, and transformed NGM (1, *N*) (TNGM (1, *N*)) [28]. These MGPMs have shown their superior prediction performance when used with time series problems.

Grey prediction has demonstrated its effectiveness on CO_2 emissions forecasting, such as univariate grey prediction models by Pao et al. [36], Wu et al. [2], and Xu et al. [37], prediction models based on trends of driving coefficients (TDVGM (1, *N*)) by Ding et al. [7], TNGM (1, *N*) by Wang and Ye [28], multikernel nonlinear multivariable grey model by Duan et al. [23], a forecasting method for the traffic-related emissions by Xie et al. [38], a nonlinear grey power model (DGPM (1, *N*)) by Ding et al. [39], and a nonequigap grey Verhulst model by Wang and Li [40]. This study contributed to developing a distinctive MGPM with feature selection and residual modification performed to improve prediction accuracy. For the former, since system performance can be improved by feature selection [41], the proposed MGPM performs grey relational analysis (GRA) [4–6, 42] to estimate relevance between independent variables and CO_2 emissions. For the latter, it has been suggested that the prediction accuracy of the GM (1, 1) can be improved by residual modification [4]. However, it is very interesting to extend residual modification to the GM (1, *N*). A neural-network-based residual model is thus created for the proposed MGPM to adjust predicted values from the GM (1, *N*). To sum up, the proposed MGPM with feature selection and residual modification can be treated as a residual modification model. Genetic algorithms (GAs) are employed to determine required parameters of the GRA and GM (1, *N*) to construct the proposed MGPM with high prediction accuracy. Experimental results have indicated that the proposed MGPM performs well compared with the other MGPMs considered. It is noted that, to estimate the correlation between the system behavior variable and the influential factors, the proposed prediction model used GA to determine a threshold value that is not easily prespecified. In contrast, Xie et al. [38] applied GRA to identify relevant factors from passenger cars per 1000 inhabitants, stock of vehicles, volume of freight transport relative to GDP (VFTRG), and volume of passenger transport relative to GDP, but only VFTRG (with time lags four) with maximum correlation was considered. Meanwhile Ding et al. [39] used a prespecified threshold value to evaluate the relationship among factors.

The remainder of the paper is organized as follows. Section 2 introduces the traditional GM (1, *N*), grey residual modification model, and Section 3 introduces the proposed MGPM with residual modification on the basis of a neural network. Section 4 examines prediction performances of the proposed MGPM using two real cases of CO_2 emissions. Section 5 discusses the outcomes and presents conclusions.

2. The GM (1, *N*) Model

The GM (1, *N*) is a grey prediction model with *N* variables, including a dependent variable (system characteristic), x_1, and $N-1$ explanatory variables (relevant factors), $x_2, x_3, \ldots, x_N$ [5]. Then, an original sequence or a time series $x_i^{(0)} = (x_i^{(0)}(1), x_i^{(0)}(2), \ldots, x_i^{(0)}(m))$ is associated with x_i, where $i = 1, 2, \ldots, N$, and m is the number of samples. $x_i^{(0)}$ is usually a sequence taken at successive equally spaced points in time.

Step 1. Present an original and nonnegative sequence $x_i^{(0)}$.

Step 2. Perform the accumulated generating operation (AGO).

A new sequence $x_i^{(1)} = (x_i^{(1)}(1), x_i^{(1)}(2), \ldots, x_i^{(1)}(m))$ can be generated from $x_i^{(0)}$ by the AGO as follows:

$$x_i^{(1)}(k) = \sum_{j=1}^{k} x_0^{(i)}, \quad k = 1, 2, \ldots, m. \tag{1}$$

The AGO can help identify potential hidden regularities in data sequences [4, 43]. $(x_i^{(1)}(1), x_i^{(1)}(2), \ldots, x_i^{(1)}(m))$ can be approximated by an exponential function, which is a first-order whitening equation,

$$\frac{\mathrm{d}x_1^{(1)}}{\mathrm{d}t} + a x_1^{(1)} = \sum_{j=2}^{N} b_j x_j^{(1)}. \tag{2}$$

where a and b_j are the development and the driving coefficients, respectively. The time response expression of $\hat{x}_k^{(1)}(k)$ $(k = 2, 3, \ldots, m)$ can be obtained by solving the differential equation with the initial condition $x_1^{(1)}(1) = x_1^{(0)}(1)$:

$$\begin{aligned}\hat{x}_1^{(1)}(k) = {} & \left(x_1^{(0)}(1) - \frac{1}{a} \sum_{j=2}^{N} b_j x_j^{(1)}(k) \right) e^{-ak} \\ & + \frac{1}{a} \sum_{j=2}^{N} b_j x_j^{(1)}(k).\end{aligned} \tag{3}$$

Step 3. Determine the development and the driving coefficients.

A grey differential equation of the GM (1, *N*) is as follows:

$$x_1^{(0)}(k) + az_1^{(1)}(k) = \sum_{j=2}^{N} b_j x_j^{(1)}(k) \quad k = 2, 3, \ldots, m. \tag{4}$$

where the background value $z_1^{(1)}(k)$ with the generating coefficient α $(0 \le \alpha \le 1)$ being usually set to 0.5 is formulated as

$$z_1^{(1)}(k) = \alpha x_1^{(1)}(k) + (1-\alpha)x_1^{(1)}(k-1), \quad k = 2, 3, \ldots, m. \tag{5}$$

Thus, a linear regression model consisting of grey differential equations is used to estimate a, $b_2, \ldots$, and b_N through the ordinary least squares (OLS) method:

$$[a, b_2, \ldots, b_N] = \left(B^T B\right)^{-1} B^T y. \tag{6}$$

where

$$B = \begin{bmatrix} -z_1^{(1)}(2) & x_2^{(1)}(2) & \cdots & x_N^{(1)}(2) \\ -z_1^{(1)}(3) & x_2^{(1)}(3) & \cdots & x_N^{(1)}(3) \\ \vdots & \vdots & \ddots & \vdots \\ -z_1^{(1)}(m) & x_2^{(1)}(m) & \cdots & x_N^{(1)}(m) \end{bmatrix}, \quad y = \begin{bmatrix} x_1^{(0)}(2) \\ x_1^{(0)}(3) \\ \vdots \\ x_1^{(0)}(m) \end{bmatrix}. \tag{7}$$

Step 4. Perform the inverse accumulated generating operation (IAGO).

When $x_i^{(1)}$ varies slightly, $\hat{x}_k^{(0)}$ can be generated by means of the IAGO:

$$\hat{x}_1^{(0)}(k) = \hat{x}_1^{(1)}(k) - \hat{x}_1^{(1)}(k), \quad k = 2, 3, \ldots, m. \tag{8}$$

where $\hat{x}_1^{(1)}(1) = x_1^{(0)}(1)$.

To improve the prediction performance of the traditional GM (1, N), several improved versions of MGPMs have been proposed by deriving new whitening and grey differential equations:

(1) The transformed model of nonlinear GM (1, N) (TNGM (1, N)) [28]: the TNGM (1, N) has been applied to forecast Chinese carbon emissions. The whitening equation of the TNGM (1, N) is defined as

$$\frac{dx_1^{(1)}}{dt} + ax_1^{(1)} = \sum_{j=2}^{N} b_j \left(x_j^{(1)}\right)^{\gamma_j}. \tag{9}$$

The solution of the whitening equation $\hat{x}_1^{(0)}(k)$ is thus given by

$$\hat{x}_1^{(0)}(k) = \frac{1}{1+0.5a} \sum_{j=2}^{N} b_j \left(x_j^{1}(k)\right)^{\gamma_j} - \frac{a}{1+0.5a} \sum_{j=2}^{N} x_1^{(1)}(k-1). \tag{10}$$

a, $b_2, \ldots$, and b_N can be further derived by OLS as

$$[a, b_2, \ldots, b_N] = \left(B^T B\right)^{-1} B^T y. \tag{11}$$

where

$$B = \begin{bmatrix} -z_1^{(1)}(2) & \left(x_2^{(1)}(2)\right)^{\gamma_2} & \cdots & \left(x_N^{(1)}(2)\right)^{\gamma_N} \\ -z_1^{(1)}(3) & \left(x_2^{(1)}(3)\right)^{\gamma_2} & \cdots & \left(x_N^{(1)}(3)\right)^{\gamma_N} \\ \vdots & \vdots & \ddots & \vdots \\ -z_1^{(1)}(m) & \left(x_2^{(1)}(m)\right)^{\gamma_2} & \cdots & \left(x_N^{(1)}(m)\right)^{\gamma_N} \end{bmatrix}. \tag{12}$$

Any optimization technique such as a GA can be used to derive the optimal γ_2, $\gamma_3, \ldots$, and γ_N.

(2) The optimization of the GM (1, N) (OGM (1, N)) [35]: the grey difference equation of the OGM (1, N) is defined as

$$x_1^{(0)}(k) + az_1^{(1)}(k) = \sum_{j=2}^{N} b_j x_j^{(1)}(k) + h_1(k-1) + h_2, \quad k = 2, 3, \ldots, m. \tag{13}$$

The time response expression of $\hat{x}_1^{(1)}(k)$ is thus given by

$$\hat{x}_1^{(1)}(k) = \sum_{j=2}^{k} \left[\mu_1 \sum_{m=2}^{N} \mu_2^{j-1} b_m x_m^{(1)}(k-j+1)\right] + \mu_2^{k-1} x_1^{(0)}(1) + \sum_{j=0}^{k-2} \mu_2^{j}\left[(k-j)\mu_3 + \mu_4\right]. \tag{14}$$

where

$$\mu_1 = \frac{1}{1+0.5a}, \quad \mu_2 = \frac{1-0.5a}{1+0.5a}, \quad \mu_3 = \frac{h_1}{1+0.5a}, \quad \mu_4 = \frac{h_2 - h_1}{1+0.5a}. \tag{15}$$

a, $b_2, \ldots, b_N$, h_1, and h_2 can be obtained by OLS as

$$[a, b_2, \ldots, b_N, h_1, h_2] = \left(B^T B\right)^{-1} B^T y, \tag{16}$$

where

$$B = \begin{bmatrix} -z_1^{(1)}(2) & x_2^{(1)}(2) & \cdots & x_N^{(1)}(2) & 1 & 1 \\ -z_1^{(1)}(3) & x_2^{(1)}(3) & \cdots & x_N^{(1)}(3) & 2 & 1 \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\ -z_1^{(1)}(m) & x_2^{(1)}(m) & \cdots & x_N^{(1)}(m) & m-1 & 1 \end{bmatrix}. \tag{17}$$

Zeng et al. [25] applied a variant of the OGM (1, N) to forecast the number of motor vehicles in Beijing.

(3) The MGPM based on trends of driving coefficients (TDVGM (1, N)) [7]: the development of the TDVGM (1, N) addressed an issue of forecasting Chinese CO_2 emissions. This prediction model initially divided data from the first year by data from each year. Then, it predicted trends of driving coefficients by defining the grey differential equation for b_j ($j = 2, 3, \ldots, N$) as

$$x_j^{(0)}(k) + a_j z_j^{(1)}(k) = b_j. \tag{18}$$

The time response expression of $\widehat{x}_j^{(1)}(k)$ is formulated as

$$\widehat{x}_j^{(1)}(k) = \left(1 - \frac{b_j}{a_j}\right) e^{-aj(k-1)} + \frac{b_j}{a_j}, \quad k = 2, 3, \ldots, m. \tag{19}$$

a_j and b_j were obtained by OLS as

$$\left[a_j, b_j\right] = \left(B^T B\right)^{-1} B^T y, \tag{20}$$

where

$$B = \begin{bmatrix} -z_1^{(1)}(2), & 1, \\ -z_1^{(1)}(3), & 1, \\ \vdots & \vdots \\ -z_1^{(1)}(m), & 1. \end{bmatrix} \tag{21}$$

Then, a time response expression of $\widehat{x}_1^{(1)}(k)$ can be derived as

$$\widehat{x}_1^{(1)}(k) = ce^{-ak} + \left(\sum_{j=2}^{N} \frac{d_j\left(\left(1 - b_j\right)/a_j\right)}{a - a_j} e^{-a_j(k-1)}\right) e^{-ak} + \sum_{j=2}^{N} \frac{d_j b_j}{a a_j}. \tag{22}$$

where

$$c = ce^{-ak} + \frac{\sum_{k=1}^{m} e^{-ak}\left(x_1^{(0)}(k) - \sum_{j=2}^{N} d_j\left(1 - b_j/a_j\right)/a - a_j\left(1 - e^{a_j}\right)e^{-a_j(k-1)}\right)}{\sum_{k=1}^{n}\left(1 - e^{a}\right)^2 e^{-2ak}}. \tag{23}$$

3. The Proposed Multivariate Grey Prediction Model

For the proposed MGPM, GRA was first used to keep explanatory variables that are more relevant to CO_2 emissions. Then, the proposed MGPM can be constructed by GAs. Subsequently, a residual GM (1, 1) model can be embedded into the proposed MGPM by establishing a functional-link net to adjust $\widehat{x}_1^{(0)}(k)$.

3.1. Feature Selection by Grey Relational Analysis. In contrast to statistical correlation analysis that measures the relationship between any two random variables, GRA can effectively measure the relationships between one reference sequence and the other comparative sequences by viewing the reference sequence as the desired goal [44]. The grey relational coefficient, ξ_{jk}, for the time period k ($1 \le j \le N-1$, $1 \le k \le m$) is addressed by the discriminative coefficient ρ ($0 \le \rho \le 1$) to indicate the relationship between $x_j^{(0)}(k)$ and $x_1^{(0)}(k)$:

$$\xi jk = \frac{\Delta_{\min} + \rho\Delta_{\max}}{\Delta_{jk} + \rho\Delta_{\max}}, \tag{24}$$

where ρ is usually specified as 0.5 and

$$\begin{aligned} \Delta \min &= \min_{j=1,\ldots,N-1} \min_{k=1,\ldots,m} \left|x_1^{(0)}(k) - x_j^{(0)}(k)\right|, \\ \Delta \min &= \max_{j=1,\ldots,N-1} \max_{k=1,\ldots,m} \left|x_1^{(0)}(k) - x_j^{(0)}(k)\right|, \\ \Delta jk &= \left|x_1^{(0)}(k) - x_j^{(0)}(k)\right|. \end{aligned} \tag{25}$$

It is seen that ξ_{jk} lies in [0, 1] and approaches 1 if Δ_{jk} approaches $\Delta_{\min}$.

To measure the degree of proximity between x_j and x_1, the grey relational grade (GRG) γ_j can be calculated as follows:

$$\gamma_j = \frac{1}{m} \sum_{k=1}^{m} \xi_{ik}, \tag{26}$$

where γ_j ranges from 0 to 1. The greater the value of γ_i is, the more relevant x_j is to x_1. In other words, to construct the proposed model, x_j can be retained for constructing the proposed MGPM when γ_j surpasses a threshold value λ; otherwise, x_j can no longer be considered for the proposed MGPM. That means, for equation (3), both b_j and $x_j^{(1)}(k+1)$ associated with x_j can be retained when γ_j is above λ; otherwise, they can be removed directly. However, λ may not be prespecified easily beforehand.

3.2. Construction of Multivariate Grey Prediction Models Using Genetic Algorithms. This study aims to find the optimal solution to construct the proposed MGPM with high prediction accuracy. This problem can be thus formulated as the following single objective optimization problem by minimizing the mean absolute percentage error (MAPE):

$$\text{Minimize}\,\frac{1}{m-1}\sum_{k=2}^{m}\frac{\left|x_1^{(0)}(k)-\hat{x}_1^{(0)}(k)\right|}{x_1^{(0)}(k)}. \quad (27)$$

Instead of OLS, a real-valued GA using MAPE as its fitness function can be developed to automatically determine the optimal values of development coefficient (a), the driving coefficients ($b_2, b_3, \ldots, b_N$), and the cut value (λ).

For the GA, a set of strings making up a population is generated initially. All parameters for each string are randomly generated as real numbers. Using the Genetic Algorithm and the Direct Search Toolbox in MATLAB, a real-valued GA is easily developed to automatically determine all parameters. The best chromosome with the maximum fitness value of all successive generations is the desired solution for examining the generalizability of the proposed MGPM.

3.3. Residual Modification Using a Functional-Link Net. $\hat{x}_1^{(0)}(k)$ produced by the proposed MGPM can be further adjusted by residual modification to improve prediction accuracy. Let $\varepsilon_1^{(0)}=(\varepsilon_1^{(0)}(2),\varepsilon_1^{(0)}(3),\ldots,\varepsilon_1^{(0)}(m))$ denote the sequence of absolute residual values, where

$$\varepsilon_1^{(0)}(k)=\left|\varepsilon_1^{(0)}(k)-\hat{\varepsilon}_1^{(0)}\right|,\quad k=2,3,\ldots,m. \quad (28)$$

Because no dependent variables are considered for ε_1, a residual GM (1, 1) model can be established for $\varepsilon_1^{(0)}$, where the predicted value of $\varepsilon_1^{(0)}(k)$ is

$$\hat{\varepsilon}_1^{(0)}(k)=\left(1-e^{a_\varepsilon}\right)\left(\varepsilon_1^{(0)}(2)-\frac{b_\varepsilon}{a_\varepsilon}\right)e^{-ae(k-1)},\quad k=3,4,\ldots,m, \quad (29)$$

where a_ε and b_ε are the developing coefficient and the control variable, respectively. $\hat{\varepsilon}_1^{(1)}(2)=\varepsilon_1^{(0)}(2)$. The problem of constructing a residual GM (1, 1) model can be formulated as the following single objective optimization problem by minimizing the MAPE:

$$\text{Minimize}\sum_{k=3}^{m}\frac{\left|\varepsilon_1^{(0)}(k)-\hat{\varepsilon}_1^{(0)}(k)\right|}{\varepsilon_1^{(0)}(k)}. \quad (30)$$

MAPE can be used as the fitness function of a real-valued GA that is used to determine optimal a_ε and b_ε instead of OLS.

Then, following a mechanism of residual modification recommended by Wang and Hu [41], the final predicted value $\hat{x}_k^{(0)}$ of the proposed MGPM is produced by means of $\hat{x}_1^{(0)}(k)$:

$$\hat{x}_1^{(0)}(k)=\hat{x}_1^{(0)}(k)+3y_k\hat{\varepsilon}_1^{(0)}(k),\quad k=2,3,\ldots,n, \quad (31)$$

where y_k ranges from −1 to 1 and can be computed by presenting (t_k, sin (πt_k), cos (πt_k), sin ($2\pi t_k$), and cos ($2\pi t_k$)) to a single-layer perceptron, namely, the functional-link net, with effective function approximation capability [45–48]:

$$\begin{aligned}y_k=\tanh\left(w_1t_k+w_2\sin\left(\pi t_k\right)+w_3\cos\left(\pi t_k\right)\right.\\ \left.+w_4\sin\left(2\pi t_k\right)+w_5\cos\left(2\pi t_k\right)+\theta\right),\end{aligned} \quad (32)$$

where tan$h$ represents a hyperbolic tangent function, and $w_1,\ldots,w_5$ are connection weights. This means that the amount of adjusting $\hat{x}_k^{(0)}$ could be as much as $3\hat{\varepsilon}_k^{(0)}$ if $y_k=1$. In contrast, the adjustable amount can be $-3\hat{\varepsilon}_k^{(0)}$ if $y_k=-1$.

4. Empirical Results

Empirical studies were conducted using real datasets to compare the CO_2 emission forecasting ability of the proposed MGPM with the other MGPMs considered. As mentioned above, urban population (UP), GDP, and energy consumption have a dominant influence on CO_2 emissions. In addition to the traditional GM (1, N), the Autoregressive Integrated Moving Average model (ARIMA) and the aforementioned improved MGPMs with comprehensible distinctive features were considered.

4.1. Case I. Statistics from the IEA [3] revealed that, in 2015, the total amount of CO_2 emissions in China was 9,040 million tons, reaching the highest level worldwide. To devise energy plans that would effectively reduce CO_2 emissions while promoting green economic growth, the ability to predict CO_2 emissions has played a very significant role in China. Therefore, we were intrigued to examine the prediction performance of MGPMs that consider CO_2 emissions in China. The data on urban population (million persons) and GDP (million USD dollars) were collected from the World Bank (http://data.worldbank.org.cn), and energy consumption (million tons of oil equivalent) and CO_2 emissions (million tons) were collected from the IEA (http://www.iea.org).

As shown in Table 1, the historical annual data were collected from 2005 to 2015, data from 2005 to 2012 were used for the model-fitting, and data from 2013 to 2015 were used for ex-post testing. Results shown in Table 2 are summarized as follows:

(1) The MAPE of the traditional GM (1, N), the TNGM (1, N), the OGM (1, N), the TDVGM (1, N), the ARIMA, and the proposed MGPM for model-fitting were 3.34%, 0.81%, 0.02%, 3.14%, 1.98%, and 1.71%, respectively. The OGM (1, N) thus demonstrated its superiority in model-fitting.

Table 1: Annual carbon dioxide emissions with GDP, UP, and EC in China.

Year	GDP	UP	EC	CO_2
2005	2285966	554.37	1184.158	5357.71
2006	2752132	575.12	1273.683	5911.96
2007	3552182	595.67	1368.733	6468.27
2008	4598206	616.48	1417.323	6608.14
2009	5109954	637.41	1480.672	7025.82
2010	6100620	658.50	1578.852	7706.65
2011	7572554	679.77	1692.063	8465.64
2012	8560547	700.86	1747.103	8620.58
2013	9607224	721.69	1816.852	8995.79
2014	10482372	742.30	1868.17	9036.47
2015	11064666	762.59	1905.679	9040.74

Table 2: MAPE (%) obtained by different MGPMs for carbon dioxide emissions in China.

Year	Actual	GM (1, *N*)		TNGM (1, *N*)		OGM (1, *N*)		TDVGM (1, *N*)		ARIMA		The proposed MGPM	
		Predicted	APE	Predicted	APE	Predicted	APE	Predicted	APE	Predicted	APE	Predicted	APE
2005	5357.7	5357.7	0.00	5357.7	0.00	5357.7	0.00	5435.9	1.32	5357.71	0.00	5357.7	0.00
2006	5912.0	5007.9	15.29	5869.3	0.72	5912.1	0.00	5786.9	2.12	5916.89	0.08	5919.4	0.13
2007	6468.3	6941.3	7.31	6478.3	0.15	6467.7	0.01	6160.3	4.76	6437.24	0.48	6850.5	5.91
2008	6608.1	6753.8	2.20	6495.6	1.70	6609.7	0.02	6551.9	0.85	6919.37	4.71	6739.0	1.98
2009	7025.8	7003.8	0.31	7083.0	0.81	7023.3	0.04	6962.3	0.90	7366.09	4.84	7026.6	0.01
2010	7706.7	7651.5	0.72	7703.0	0.05	7709.3	0.03	7390.9	4.10	7779.98	0.95	7556.9	1.94
2011	8465.6	8429.1	0.43	8255.0	2.49	8464.0	0.02	7838.3	7.41	8163.48	3.57	8186.0	3.30
2012	8620.6	8660.7	0.47	8665.3	0.52	8621.1	0.01	8303.9	3.67	8518.80	1.18	8582.9	0.44
MAPE	—	—	3.34	—	0.81	—	0.02	—	3.14	—	1.98	—	1.71
2013	8995.8	9039.7	0.49	9011.6	0.18	9080.8	0.94	8788.2	2.31	8848.02	1.64	8990.6	0.06
2014	9036.5	9248.2	2.34	9270.5	2.59	9282.2	2.72	9290.3	2.81	9153.05	1.29	9242.6	2.28
2015	9040.7	9342.8	3.34	9452.7	4.56	9419.1	4.19	9809.9	8.51	9435.68	4.37	9335.2	3.26
MAPE	—	—	2.06	—	2.44	—	2.62	—	4.54	—	2.43	—	1.87

(2) For ex-post testing, the MAPE of the traditional GM (1, *N*), the TNGM (1, *N*), the OGM (1, *N*), the TDVGM (1, *N*), the ARIMA, and the proposed MGPM were 2.06%, 2.44%, 2.62%, 4.54%, 2.43%, and 1.87%, respectively.

(3) Although the proposed MGPM is inferior to the TNGM (1, *N*) and the OGM (1, *N*) for model-fitting, it is superior to other MGPMs considered for ex-post testing.

It should be noted that, when evaluating a prediction model, more emphasis should be placed on generalization rather than on model-fitting [49]. Figure 1 also demonstrates the superiority of the generalization ability of the proposed MGPM over the other prediction models considered.

4.2. Case II. From statistics reported by the IEA [47], the total and average amounts of CO_2 emissions in Taiwan in 2015 were the 21st and the 19th highest in the world, respectively. This means that Taiwan still has room to reduce CO_2 emissions. The second real case involved the historical annual CO_2 emission data collected in Taiwan from 2005 to 2015. The data on urban population (million persons) and GDP (million USD dollars) were collected from the United Nations Conference on Trade and Development (UNCTAD) (http://unctad.org/en/Pages/statistics.aspx), and energy consumption (million tons of oil equivalent) and CO_2 emissions (million tons) were collected from the IEA.

As shown in Table 3, data collected from 2005 to 2012 were used for the model-fitting, and data from 2013 to 2015 were used for ex-post testing. The results obtained from the different prediction models are shown in Table 4. The results are summarized as follows:

(1) The MAPE of the traditional GM (1, *N*), the TNGM (1, *N*), the OGM (1, *N*), the TDVGM (1, *N*), the ARIMA, and the proposed MGPM for model-fitting were 3.35%, 0.23%, 0.21%, 2.59%, 2.10%, and 1.86%, respectively. The TNGM (1, *N*) and the OGM (1, N) demonstrated their superiority in model-fitting.

(2) The MAPE of the traditional GM (1, *N*), the TNGM (1, *N*), the OGM (1, *N*), the TDVGM (1, *N*), the ARIMA, and the proposed MGPM for ex-post testing were 1.28%, 4.75%, 8.43%, 4.54%, 0.86%, and 1.09%, respectively. The proposed MGPM is slightly inferior to the TDVGM (1, *N*).

(3) Although the proposed MGPM is inferior to the TNGM (1, *N*) and the OGM (1, *N*) for model-fitting, it is superior to those two MGPMs for ex-post testing.

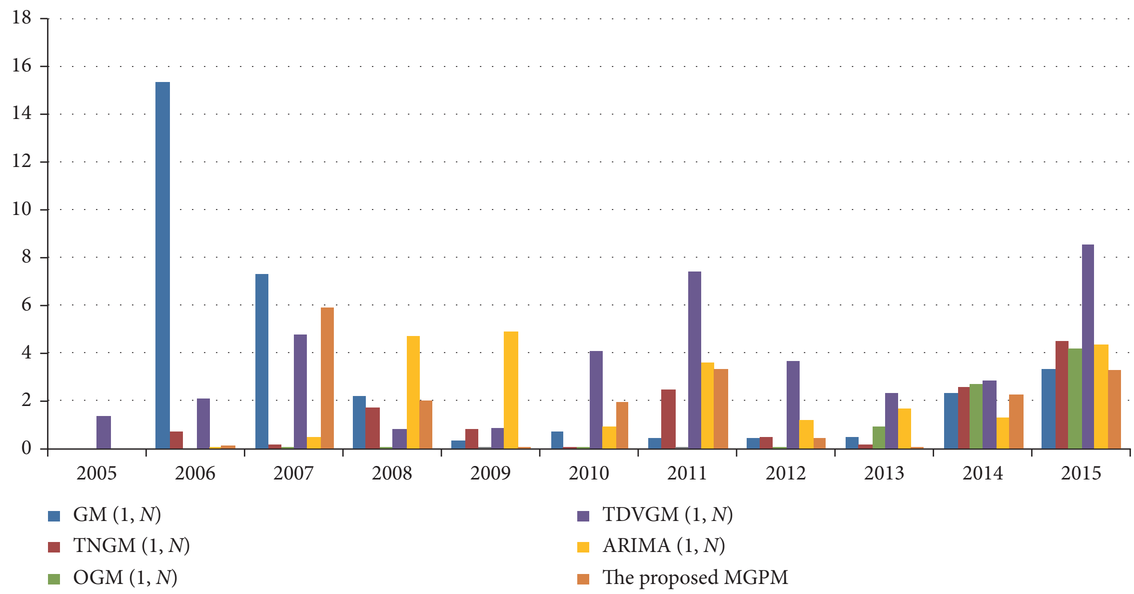

Figure 1: Comparisons between different MGPMs for carbon dioxide emissions prediction in China.

Table 3: Annual carbon dioxide emissions with GDP, UP, and EC in Taiwan.

Year	GDP	UP	EC	CO_2
2005	375787	22.603	60.437	253.64
2006	388547	22.725	61.276	260.86
2007	408221	22.833	65.511	263.94
2008	417038	22.929	63.393	252.75
2009	392106	23.017	62.892	239.68
2010	446141	23.102	67.855	256.22
2011	485671	23.185	65.405	254.7
2012	495919	23.264	65.289	246.55
2013	511599	23.34	67.808	247.59
2014	530515	23.414	68.014	249.66
2015	525236	23.486	68.566	249.38

Table 4: MAPE (%) obtained by different MGPMs for carbon dioxide emissions in Taiwan.

Year	Actual	GM (1, N)		TNGM (1, N)		OGM (1, N)		TDVGM (1, N)		ARIMA		The proposed MGPM	
		Predicted	APE	Predicted	APE	Predicted	APE	Predicted	APE	Predicted	APE	Predicted	APE
2005	253.64	253.64	0.00	253.64	0.00	253.64	0.00	250.18	1.36	253.64	0.00	253.64	0.00
2006	260.86	220.24	15.57	260.33	0.20	260.38	0.18	250.79	3.86	255.91	1.90	261.36	0.19
2007	263.94	270.58	2.52	264.40	0.17	264.29	0.13	251.06	4.88	251.58	4.68	258.87	1.92
2008	252.75	253.11	0.14	253.18	0.17	252.48	0.11	251.24	0.60	252.39	0.14	249.56	1.26
2009	239.68	252.71	5.44	239.68	0.00	239.66	0.01	251.36	4.87	252.24	5.24	233.84	2.44
2010	256.22	256.63	0.16	255.82	0.16	256.81	0.23	251.43	1.87	252.26	1.54	250.40	2.27
2011	254.70	249.01	2.23	252.97	0.68	252.88	0.71	251.43	1.28	252.26	0.96	241.07	5.35
2012	246.55	248.41	0.75	247.71	0.47	247.24	0.28	251.37	1.95	252.26	2.32	242.89	1.48
MAPE	—	—	3.35	—	0.23	—	0.21	—	2.59	—	2.10	—	1.86
2013	253.64	251.97	1.77	254.77	2.90	257.98	4.20	251.24	1.47	252.26	1.89	249.91	0.94
2014	260.86	251.07	0.56	260.44	4.32	268.40	7.51	251.04	0.55	252.26	1.04	251.72	0.83
2015	263.94	253.13	1.50	266.89	7.02	283.29	13.60	250.77	0.56	252.26	1.15	253.15	1.51
MAPE	—	—	1.28	—	4.75	—	8.43	—	0.86	—	1.36	—	1.09

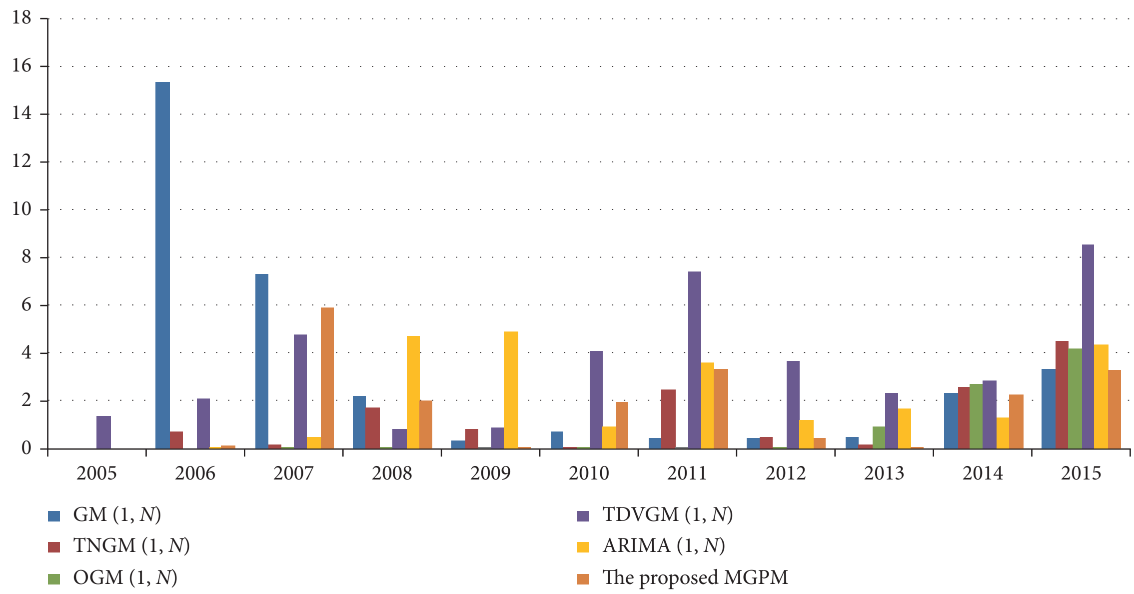

Figure 2: Comparisons between different MGPMs for carbon dioxide emissions prediction in Taiwan.

In Figure 2, we can see that the proposed MGPM performs well compared with other prediction models considered.

5. Discussion

What this study focuses on is the forecast rather than the projection. Compared with the projection, the forecast places value on estimating the amount of CO_2 emissions based on an established model such as a MGPM for which MAPE is a useful metric for measuring the prediction performance [50]. The projection can answer "what-if" kind of questions to extrapolate the development trend. In other words, it is concerned about what would happen to CO_2 emission based on some future scenarios, for instance, how CO_2 is produced and how it is influenced by what kind of factors.

As mentioned above, the forecast of CO_2 emissions can be regarded as a grey system problem. Furthermore, CO_2 emission data might well not conform to statistical assumptions. Therefore, it is reasonable to apply MGPMs to forecast the amount of CO_2 emissions. Compared with the other MGPMs, feature selection and residual modification are taken into account in the proposed MGPM to improve prediction accuracy. In particular, GRA and a functional-link net are employed to implement feature selection and residual modification, respectively. The empirical results reveal that feature selection and residual modification can boost the prediction performance of the proposed MGPM. It is noted that although the OGM (1, N) variant [25] also applied GRA to filter out irrelevant features, the cut value (λ) was arbitrarily assigned by a prespecified value. However, λ can be optimized by the GA to improve the prediction accuracy of the proposed MGPM.

With real-world datasets, from Tables 2 and 4, we can see that the generalization ability of the proposed MGPM for CO_2 emissions was quite encouraging. The outcomes verified that the results obtained by the proposed MGPM are comparable to other prediction models considered. It is interesting to note that the TNGM (1, N) and the OGM (1, N) are superior to the traditional GM (1, N) and the proposed MGPM for model-fitting but inferior for ex-post testing. In other words, both the TNGM (1, N) and the OGM (1, N) appear to be overfitting. Experimental results show that the fitting and generalization abilities of the proposed MGPM are superior to the traditional GM (1, N). Thus, the prediction ability of the traditional GM (1, N) could be effectively improved by feature selection and residual modification indeed.

6. Conclusions

Undoubtedly, the reduction of greenhouse gas emissions is critical to environmental protection. For many countries, CO_2 is mainly produced from fuel combustion, which forms the majority of greenhouse gases. How to reduce the impact that energy consumption and economic growth have on CO_2 emissions has gained increasing global attention. Revelations from the IEA [3] showed that, along with global economic growth, global CO_2 emissions plateaued from 2014 to 2016 due to the growth of renewable electricity, the replacement of coal with natural gas, and changes to the economic structure. There appeared to be a decoupling of economic growth and environmental degradation. However, this does not mean that CO_2 emissions have reached a summit. To continuously inhibit carbon emissions and remain competitive, it is necessary for the authorities to make use of prediction models on carbon emissions, set up comprehensive policies on the development of new energy technologies, and increase demand for renewable energies (e.g., solar, wind, and natural gas) and environmental protection.

In addition to CO_2 emissions, there are several multivariate prediction problems, such as energy demand forecasting, which need to be resolved. In fact, energy demand prediction has become increasingly important when devising development plans for a country, particularly for developing countries [51]. Meanwhile, energy demand forecasting can be regarded as a grey system problem [52] because a few factors, such as income and population, have an influence on energy demand, but how exactly these factors affect energy demand is not clear. On the basis of the conspicuous forecasting performance of the proposed MGPM for CO_2 emissions, it would be interesting to explore its applicability to energy demand forecasting.

Data Availability

Statistics used in this paper are from the IEA (International Energy Agency).

Conflicts of Interest

The authors declare that there are no conflicts of interest.

Acknowledgments

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References

[1] P. Nema, S. Nema, and P. Roy, “An overview of global climate changing in current scenario and mitigation action,” *Renewable and Sustainable Energy Reviews*, vol. 16, no. 4, pp. 2329–2336, 2012.

[2] W. Wu, X. Ma, Y. Zhang, and Y. Wang, “A novel conformable fractional non-homogeneous grey model for forecasting carbon dioxide emissions of BRICS countries,” *Science of The Total Environmen*, vol. 707, p. 13544, 2020.

[3] International Energy Agency, *Key World Energy Statistics 2017*, IEA/OECD, Paris, France, 2019.

[4] S. Liu and Y. Lin, *Grey Information: Theory and Practical Applications*, Springer, Berlin, Germany, 2010.

[5] S. Liu, Y. Yang, and J. Forrest, *Grey Data Analysis: Methods, Models and Applications*, Springer, Berlin, Germany, 2017.

[6] J. L. Deng, “Control problems of grey systems,” *Systems and Control Letters*, vol. 1, no. 5, pp. 288–294, 1982.

[7] S. Ding, Y.-G. Dang, X.-M. Li, J.-J. Wang, and K. Zhao, “Forecasting Chinese CO2 emissions from fuel combustion using a novel grey multivariable model,” *Journal of Cleaner Production*, vol. 162, pp. 1527–1538, 2017.

[8] L. Wu, S. Liu, D. Liu, Z. Fang, and H. Xu, “Modelling and forecasting CO 2 emissions in the BRICS (Brazil, Russia, India, China, and South Africa) countries using a novel multi-variable grey model,” *Energy*, vol. 79, pp. 489–495, 2015.

[9] O. Burcu, “The nexus between carbon emissions, energy consumption and economic growth in Middle East countries: a panel data analysis,” *Energy Policy*, vol. 62, pp. 1138–1147, 2013.

[10] P. A. González and J. M. Zamarreño, “Prediction of hourly energy consumption in buildings based on a feedback artificial neural network,” *Energy and Buildings*, vol. 37, no. 6, pp. 595–601, 2005.

[11] P. Lauret, E. Fock, R. N. Randrianarivony, and J.-F. Manicom-Ramsamy, “Bayesian neural network approach to short time load forecasting,” *Energy Conversion and Management*, vol. 49, no. 5, pp. 1156–1166, 2008.

[12] C. Xia, J. Wang, and K. McMenemy, “Short, medium and long term load forecasting model and virtual load forecaster based on radial basis function neural networks,” *International Journal of Electrical Power & Energy Systems*, vol. 32, no. 7, pp. 743–750, 2010.

[13] W. Sun and M. Liu, “Prediction and analysis of the three major industries and residential consumption CO2 emissions based on least squares support vector machine in China,” *Journal of Cleaner Production*, vol. 122, pp. 144–153, 2016.

[14] O. Kaynar, I. Yilmaz, and F. Demirkoparan, “Forecasting of natural gas consumption with neural network and neuro fuzzy system,” *Energy Education Science and Technology Part A: Energy Science and Research*, vol. 26, pp. 221–238, 2011.

[15] R. Li, X. Chen, T. Balezentis, D. Streimikiene, and Z. Niu, “Multi-step least squares support vector machine modeling approach for forecasting short-term electricity demand with application,” *Neural Computing and Applications*, 2020.

[16] M. Meng and D. Niu, “Modeling CO_2 emissions from fossil fuel combustion using the logistic equation,” *Energy*, vol. 36, no. 5, pp. 3355–3359, 2011.

[17] A. Azadeh, M. Khakestani, and M. Saberi, “A flexible fuzzy regression algorithm for forecasting oil consumption estimation,” *Energy Policy*, vol. 37, no. 12, pp. 5567–5579, 2009.

[18] Q. Yan, W. Zhang, J. Yuan, T. Balezentis, and Y. Zhang, “How much electricity will be consumed in 2020 under the new normal economy in China?” *Transformations in Business & Economics*, vol. 18, no. 2, pp. 88–102, 2019.

[19] V. Ş. Ediger and S. Akar, “ARIMA forecasting of primary energy demand by fuel in Turkey,” *Energy Policy*, vol. 35, no. 3, pp. 1701–1708, 2007.

[20] S. Tutun, C.-A. Chou, and E. Canıyılmaz, “A new forecasting framework for volatile behavior in net electricity consumption: a case study in Turkey,” *Energy*, vol. 93, pp. 2406–2422, 2015.

[21] C.-H. Wang and L.-C. Hsu, “Using genetic algorithms grey theory to forecast high technology industrial output,” *Applied Mathematics and Computation*, vol. 195, no. 1, pp. 256–263, 2008.

[22] K. L. Wen, *Grey Systems Modeling and Prediction*, Yang’s Scientific Research Institute, Tucson, AZ, USA, 2004.

[23] H. Duan, D. Wang, X. Pang, Y. Liu, and S. Zeng, “A novel forecasting approach based on multi-kernel nonlinear multivariable grey model: a case report,” *Journal of Cleaner Production*, vol. 260, 2020.

[24] M. Guo, J. Lan, J. Li, Z. Lin, and X. Sun, “Traffic flow data recovery algorithm based on gray residual GM (1, N) model,” *Journal of Transportation Systems Engineering and Information Technology*, vol. 12, no. 1, pp. 42–47, 2012.

[25] B. Zeng, C. Luo, S. Liu, and C. Li, “A novel multi-variable grey forecasting model and its application in forecasting the amount of motor vehicles in Beijing,” *Computers & Industrial Engineering*, vol. 101, pp. 479–489, 2016.

[26] Z.-X. Wang, “A GM (1, N)-based economic cybernetics model for the high-tech industries in China,” *Kybernetes*, vol. 43, no. 5, pp. 672–685, 2014.

[27] L. L. Pei, W. M. Chen, J. H. Bai, and Z. X. Wang, "The improved GM (1, *N*) models with optimal background values: a case study of Chinese high-tech industry," *The Journal of Grey System*, vol. 27, no. 3, pp. 223–233, 2015.

[28] Z.-X. Wang and D.-J. Ye, "Forecasting Chinese carbon emissions from fossil energy consumption using non-linear grey multivariable models," *Journal of Cleaner Production*, vol. 142, pp. 600–612, 2017.

[29] Z. X. Wang and P. Hao, "An improved grey multivariable model for predicting industrial energy consumption in China," *Applied Mathematical Modelling*, vol. 40, no. 11-12, pp. 5745–5758, 2016.

[30] L. C. Hsu, "Forecasting the output of integrated circuit industry using genetic algorithm based multivariable grey optimization models," *Expert Systems with Applications*, vol. 36, no. 2, pp. 7898–7903, 2009.

[31] L.-C. Hsu and C.-H. Wang, "Forecasting integrated circuit output using multivariate grey model and grey relational analysis," *Expert Systems with Applications*, vol. 36, no. 2, pp. 1403–1409, 2009.

[32] H. Jiang and Y.-C. Hu, J.-Y. Lin and P. Jiang, "Analyzing China's OFDI using a novel multivariate grey prediction model with Fourier series" *International Journal of Intelligent Computing and Cybernetics*, vol. 12, no. 3, pp. 352–371, 2019.

[33] W. B. Wang and Y. C. Hu, "Multivariate grey prediction models for pattern classification irrespective of time series," *Journal of Grey System*, vol. 31, no. 2, pp. 135–142, 2019.

[34] Y.-C. Hu, "A multivariate grey prediction model with grey relational analysis for bankruptcy prediction problems," *Soft Computing*, vol. 24, no. 6, pp. 4259–4268, 2020.

[35] B. Zeng, C. Luo, S. Liu, Y. Bai, and C. Li, "Development of an optimization method for the GM (1, *N*) model," *Engineering Applications of Artificial Intelligence*, vol. 55, pp. 353–362, 2016.

[36] H.-T. Pao, H.-C. Fu, and C.-L. Tseng, "Forecasting of CO2 emissions, energy consumption and economic growth in China using an improved grey model," *Energy*, vol. 40, no. 1, pp. 400–409, 2012.

[37] N. Xu, S. Ding, Y. Gong, and J. Bai, "Forecasting Chinese greenhouse gas emissions from energy consumption using a novel grey rolling model," *Energy*, vol. 175, pp. 218–227, 2019.

[38] M. Xie, L. Wu, B. Li, and Z. Li, "A novel hybrid multivariate nonlinear grey model for forecasting the traffic-related emissions," *Applied Mathematical Modelling*, vol. 77, pp. 1242–1254, 2020.

[39] S. Ding, N. Xu, J. Ye, W. Zhou, and X. Zhang, "Estimating Chinese energy-related CO2 emissions by employing a novel discrete grey prediction model," *Journal of Cleaner Production*, vol. 259, Article ID 120793, 2020.

[40] Z.-X. Wang and Q. Li, "Modelling the nonlinear relationship between CO2 emissions and economic growth using a PSO algorithm-based grey Verhulst model," *Journal of Cleaner Production*, vol. 207, pp. 214–224, 2019.

[41] W. B. Wang and Y. C. Hu, "A novel grey residual modification model using neural networks," *Journal of Grey System*, vol. 30, no. 4, pp. 34–46, 2018.

[42] Y.-C. Hu, "A novel flow-based method using grey relational analysis for pattern classification," *International Journal of Information Technology & Decision Making*, vol. 12, no. 1, pp. 75–93, 2013.

[43] S. J. Feng, Y. D. Ma, Z. L. Song, and J. Ying, "Forecasting the energy consumption of China by the grey prediction model," *Energy Sources, Part B: Economics, Planning, and Policy*, vol. 7, no. 4, pp. 376–389, 2012.

[44] Y.-C. Hu, R.-S. Chen, Y.-T. Hsu, and G.-H. Tzeng, "Grey self-organizing feature maps," *Neurocomputing*, vol. 48, no. 1–4, pp. 863–877, 2002.

[45] Y. H. Pao, *Adaptive Pattern Recognition and Neural Networks*, Addison-Wesley, Boston, MA, USA, 1989.

[46] Y.-H. Pao and Y. Takefuji, "Functional-link net computing: theory, system architecture, and functionalities," *Computer*, vol. 25, no. 5, pp. 76–79, 1992.

[47] G. H. Park and Y. H. Pao, "Unconstrained word-based approach for off-line script recognition using density-based random-vector functional-link net," *Neurocomputing*, vol. 31, no. 1–4, pp. 45–65, 2000.

[48] Y.-C. Hu, "Grey prediction with residual modification using functional-link net and its application to energy demand forecasting," *Kybernetes*, vol. 46, no. 2, pp. 349–363, 2017.

[49] D. R. Luo, K. Z. Guo, and H. R. Huang, "Regional economic forecasting combination model based on RAR + SVR," *Advances in Intelligent Systems and Computing, Fuzzy Information & Engineering And Operations Research & Management*, vol. 211, pp. 329–338, 2014.

[50] S. Aminikhanghahi and D. J. Cook, "A survey of methods for time series change point detection," *Knowledge and Information Systems*, vol. 51, no. 2, pp. 339–367, 2017.

[51] D. Pi, J. Liu, and X. Qin, "A grey prediction approach to forecasting energy demand in China," *Energy Sources, Part A: Recovery, Utilization, and Environmental Effects*, vol. 32, no. 16, pp. 1517–1528, 2010.

[52] L. Suganthi and A. A. Samuel, "Energy models for demand forecasting-A review," *Renewable and Sustainable Energy Reviews*, vol. 16, no. 2, pp. 1223–1240, 2012.