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Prediction of CO_2 Emissions in Iran using Grey and ARIMA Models

Mohammad Reza Lotfalipour
Faculty of Economic and Administrative Sciences, Ferdowsi University of Mashhad, Mashhad, Iran. Email: Lotfalipour@um.ac.ir

Mohammad Ali Falahi
Faculty of Economic and Administrative Sciences, Ferdowsi University of Mashhad, Mashhad, Iran. Email: Falahi@um.ac.ir

Morteza Bastam
Corresponding Author, Faculty of Economic and Administrative Sciences, Ferdowsi University of Mashhad, Mashhad, Iran.
Email: Morteza.Bastam@stu.um.ac.ir

ABSTRACT: The examination of economic aspects of gas emissions and its consequences is very important, especially in terms of its volume at the current increasing trend. Therefore, the prediction of air pollution emissions of carbon dioxide can give the correct direction to policies adopted. Hence, studying and forecasting of gas emissions is necessary. The purpose of this paper is the prediction of CO_2 emissions based on Grey System and Autoregressive Integrated Moving Average and comparison of these two methods by RMSE, MAE and MAPE metrics. The results show the more accuracy of Grey system forecasting rather than other methods of prediction. Also, based on the estimated results, the amount of carbon dioxide emissions will reach up to 925.68 million tons in 2020 which shows an increase of 66 percent growth compared to 2010 which is highly significant.

Keywords: Carbon Dioxide Emissions; Forecasting; Grey system; Iran
JEL Classifications: C22; C53; Q50

1. Introduction

The society's increasing dependence on energy, has caused the energy to be considered as an effective factor in economic growth and development that plays a remarkable role in various sectors of the economy. Energy is known as one of the most influential factors in the economic growth theories, but its importance differs from one model to one another. In some models, such as the growth biophysical model brought up by Ayres and Nair (1984), energy has been posed a high value that assumed as the unique and most important growth factor in model specification. In this model, two inputs of capital and labor are as intermediate inputs. In other models such as Berndt's neoclassical growth model (1988), the importance of energy in growth is not as much as that in biophysical model and energy enters as a production along with capital and labor in the model. Thus, based on the entire economic growth theories, energy is considered as a key factor that it is not possible to move toward economic growth without. However, the adverse environmental effects of energy use have attracted the attention of economic theories to the pollution. Because, beside production inputs such as capital, labor and raw materials, some parts of the environment are used too. With economic growth in a country and simultaneous expansion of production and energy consumption, threats such as destruction of natural resources and pollution appear in result and so a paradox is emerged between the growth of production and environmental quality. But according to objectives of the programs such as "Agenda 21[1]" and the "Millennium Declaration[1]", destruction of natural capital should not be

[1] Agenda 21 is a global and comprehensive plan for achieving sustainable development in the twenty-first century came to pass at the year 1992 in Rio de Janeiro. Agenda 21 is an optimal model for economic development and quality improvement in the life of the present generation without natural resources being deprived for future generations and besides have attention to economic, social and environmental issues and also provide solutions for them.

persisted over time to ensure sustainable development. So, the evaluation of economic aspects of gas emissions and its consequences is so important, particularly in the very fast current uptrend.

The increasing threat of global warming and climate change has been a major, worldwide and important concern during the last two decades. The 1997 Kyoto protocol had the objective of reducing greenhouse gases (GHGs) which contributed to climate change. The reduction of GHG emissions to 5.2% lower than the 1990 level had been asked during the period between 2008 and 2012 that came into force in 2005. Amongst several environmental pollutants causing climate change, carbon dioxide (CO_2) is held responsible for 58.8% of GHGs (World Bank, 2007). According to the World Development Indicators (WDI), the world CO_2 emissions per capita are 4.7 metric tons with the growth rate of 11.9% in 2011. While the statistics show a worrying situation in Iran with the high CO_2emissions per capita and increase of its rate. So that, Iran's carbon dioxide emissions per capita reach to upper 8 metric tons, so higher than the global average. On the other hand, it is observed that the growth of CO_2 emissions during 1990-2011, with the amount 115.8 grew more than double, while this amount is 11.9 percent for the world (WDI, 2013). (See table 1).

Table 1. CO_2 emissions per capita in 2011 and its growth rate (1990-2011)

	Iran	World	Middle East & North Africa	Upper middle income group
Co_2 emissions per capita(metric tons)	8.2	4.7	4.1	5.5
Co_2 emissions growth (1990-2011)	115.8	11.9	64.0	57.14

Source: World Development Indicators (2013)

According to represented statistics, the emission of this gas is in an unsatisfactory level that endangers environmental conditions as one of the important elements to achieve sustainable development. So, abiding with commitments related on international agreements and regional cooperation for national policies on sustainability issues and achieving goals such as increasing value of life quality, have converted environment as one of the important component on relation to macro policies currently which other activities are influenced. So, studying the prediction of CO_2 emissions is essential for proper planning in order to achieve economic objectives and policies for ongoing growth and sustainable development.

In the next section, the findings of researchers in relation to Grey and Auto Regressive Integrated Moving Average (ARIMA) forecasting methods are discussed. The third section is devoted to the Methodology in which after introducing of the prediction concepts, Grey system is explained as more precise and detailed. The last section is specialized for empirical results and conclusion of the findings.

2. Literature Survey

The forecasting issues are significantly important points applied in many branches of scientific studies such as economics, agriculture, meteorology, medicine, engineering, etc. Kim and Yun (2012), Akay and Atak (2007), Huang and Jane (2009), Cao (2003), Guo et al. (2005), Huang and Tsai (2009), Hussain et al. (2008), Tan and Lu (1996), Wang (2002), Kayacan et al. (2010), Kung (2005), Li and Wang (2011), Jiang et al. (2004) and Mao et al. (2006) are some of researchers who utilized Grey model for prediction in their studies. In following, some of the papers carried out in this field are mentioned.

Recent studies have been progressed with applications of GM (1,1) in different branches. For example, Grey prediction model is used to predict the energy consumption of building by the heat-moisture system and prediction accuracy is fairly high by Wang et al. (1999). Also Tseng et al. (2001) suggested a hybrid method that combines GM with ratio to-moving- average depersonalization method to forecast time series with seasonal characteristics. Hsu (2003) explained the GM requires minimal

[1] . The Millennium Development Goals (MDGs) are eight international development goals that were officially established following the Millennium Summit of the United Nations in 2000, following the adoption of the United Nations Millennium Declaration. All 193 United Nations member states and at least 23 international organizations have agreed to achieve these goals by the year 2015.

data, and is currently the best model for making short-term predictions. Chang et al.(2005) advanced a method for Bianco et al. (2010) used Holt-Winters exponential smoothing method and a trigonometric Grey model with rolling mechanism are employed for the consumption prediction and the two models have very similar results with an average relative error of 5%. Lin and Yang (2003) used GM to predict the output value in Taiwan optoelectronics industry.

Pao and Tsai (2011) studied modeling and prediction of CO_2 emissions, energy consumption and economic growth in Brazil. They used GM[1] and ARIMA models and used the mean absolute error percentage (MAEP) to test prediction accuracy. The results show better prediction accuracy of GM model than of ARIMA. Wu (2012) in his thesis predicted the stock index based on grey theory, ARIMA and wavelet method. Then, by combining the models and using the hybrid models achieved better prediction by existing standards. Askari and Fetanat (2011), investigated the accuracy of two different Grey models including original GM (1, 1) and modified GM (1, 1) using Fourier series. The performance of these models has been compared with ARIMA as a conventional forecasting model. Numerical results show that the modified GM (1, 1) provides better performance in model fitting and model forecasting. Lin et al. (2007) studied the Grey relation performance correlations among economics, energy use and carbon dioxide emission in Taiwan and predicted these three variables by GM (1, 1) in 2007-2025.

3. Data and Methodology

In this study, in order to obtain information about the annual CO_2 emissions in Iran, British Petroleum[2] (BP) site is used. All data are in million tones and the investigation period is 1965-2010 until we predict it to 2010- 2020. We use Grey system and ARIMA models to predict it. In the following section we will explain these models.

3.1. Grey Model (GM)

Grey theory by which an information system can be classified into three categories, had been introduced for the first time by Prof. Deng (1982). This theory includes White system, Grey system and Black system. If the system is completely unknown, it is called black while a system that is fully known is called white and a grey system is the system between black and white. As an advantage of statistical experimental model, Grey system requires only limited data to estimate the behavior of an unknown system (Deng, 1989). In summary, the main aim of Grey system theory is to focus on the relation between analysis model structure and conditions such as uncertainty, multi-data input, discrete data and lack of data for forecasting and decision making. The grey models predict the future value of a time series, which are based on a set of recent data and dependent on the size of predictor. It is assumed that all of data values used in Grey model are positive and frequency of time series sample is invariant.

The main task of Gray system theory is the extraction of actual laws in system using existing data. This process is known as grey sequence generation (Lin and Liu, 2004). It is argued that even the available system data that is usually white, always contains rules which are very complex and chaotic. If the Grey system data are smoothed in some way, any specific inference features of the system will be easier.

"Grey Model First Order One Variable (GM (1, 1))" is a kind of Grey model which is the most widely used in the literature. This model is a time series prediction model. The differential equations of GM (1, 1) model have time-varying coefficient. This means that the model is renewed as the new data which is available to the forecasting model (Deng, 1989). Using Grey generating approaches in GM (1, 1) reduces the fluctuations of the original data series by transforming the data series linearly is so important. To this purpose, critical feature applied the accumulative generating operation (AGO) and the inverse accumulative generating operation (IAGO). The first converts a series lacking any obvious trend into a strictly increasing series to reduce the fluctuations of the series. For example, the following sequence, which represents in five days, is given:

$$X^{(0)} = (2, 5, 3, 4, 7)$$

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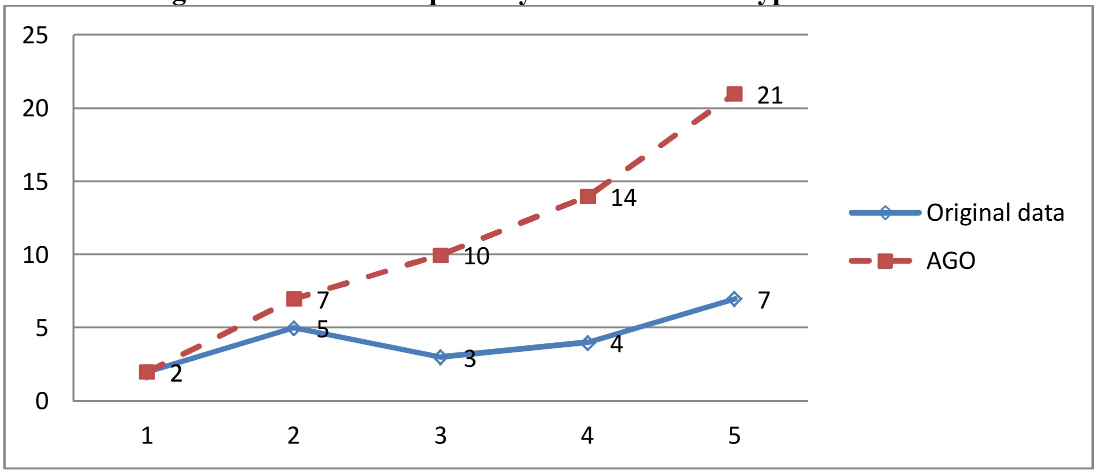
[1] . Grey Model(GM)

[2] . WWW.BP.COM

It can be seen that the sequence doesn't have a distinct discipline. So, if the AGO is proposed, then $X^{(1)}$, will show a clear growth trend. The trend of primary and cumulative Hypothetical numbers can be seen in figure [1]:

$$X^{(1)} = (2, 7, 10, 14, 21)$$

Figure 1. The trend of primary and cumulative hypothetical numbers



Differential equations such as GM (1, 1) solve prediction value of system by using *n* stages. Finally, using predicted values, IAGO are used to values predicted by original data. If sequence $X^{(0)}$ refers to the original data, we have:

$$X^{(0)} = (x^{(0)}(1), x^{(0)}(2), ..., x^{(0)}(n)), \quad n \geq 4 \qquad (1)$$

That $X^{(0)}$ is a non-negative sequence and *n* is the size of the sample. A GM (1, 1) model can be formed and operated with the use of four data (Tien, 2012). When this sequence is turned to accumulative operator, the sequence $X^{(1)}$ will emerge. It is clear that $X^{(1)}$ is steadily increasing.

$$X^{(1)} = (x^{(1)}(1), x^{(1)}(2), ..., x^{(1)}(n)), \quad n \geq 4 \qquad (2)$$

So that:

$$X^{(1)}(k) = \sum_{i=1}^{k} X^{(0)}(i), \qquad k = 1, 2, 3, ..., n \qquad (3)$$

The average sequences generator is defined as:

$$Z^{(1)} = (Z^{(1)}(1), Z^{(1)}(2), ..., Z^{(1)}(k), ..., Z^{(1)}(n)) \qquad (4)$$

In which $Z^{(1)}(k)$ is the average value of the consecutive data. In other words:

$$z^{(1)}(K) = \frac{1}{2}x^{(1)}(k) + \frac{1}{2}x^{(1)}(k-1) \qquad k = 2, 3, ..., n \qquad (5)$$

The least square estimation sequence of GM (1, 1) is expressed as follows:

$$x^{(0)}(k) + az^{(0)}(k) = b \qquad (6)$$

So whiteness equation is the following:

$$\frac{dx^{(1)}(t)}{dt} + ax^{(1)}(t) = b \qquad (7)$$

The above, [a, b] is a sequence of parameters that can be expressed as follows:

$$[a,b]^T = (B^T B)^{-1} B^T Y \qquad (8)$$

In which T is the matrix transpose. As a result:

$$Y = [x^{(0)}(2), x^{(0)}(3), ..., x^{(0)}(n)]^T \qquad (9)$$

$$B = \begin{bmatrix} -z^{(1)}(2) & 1 \\ -z^{(1)}(3) & 1 \\ \vdots & \vdots \\ -z^{(1)}(n) & 1 \end{bmatrix} \tag{10}$$

According to the equation (7), by the solution of $X^{(1)}(t)$ at k time we have:

$$x_p^{(1)}(k+1) = [x^{(0)}(1) - \frac{b}{a}]e^{-ak} + \frac{b}{a} \tag{11}$$

By applying the original predicted data at time (k+1), the IAGO will provide the grey model in equation (12):

$$x_p^{(0)}(k+1) = [x^{(0)}(1) - \frac{b}{a}]e^{-ak}(1 - e^{a}) \tag{12}$$

And the original predicted data at time (k+ H) is:

$$x_p^{(0)}(k+H) = [x^{(0)}(1) - \frac{b}{a}]e^{-a(k+H-1)}(1 - e^{a}) \tag{13}$$

Since Box – Jenkins (1976) method is one of the most popular forecasting methods that full explanation of it has been published in numerous articles. So, we just explain Hannan and Rissanen method and avoid describing it precisely.

3.2. Auto Regressive Integrated Moving Average (ARIMA)

The ARIMA (*p, d, q*) is a model with these three parameters: *d*= number of differences for stationarity. *P* = order of the AR component and *q*= order of the MA component. Typically d is zero, or very occasionally two; and one seeks a parsimonious representation with low values of p and q. The difficult choice of the order of p and q may be helped by a numerical procedure suggested by Hannan and Rissanen (1982). The procedure has three steps. In the first step, some pure AR processes of fairly high order are estimated via Ordinary Least Square (OLS) method, which is not unreasonable since an unknown ARMA process is equivalent to an infinite AR process. The regression with the smallest value of the Akaike information criterion (AIC) is selected in step two, and the residuals from this regression are taken as estimates of the unknown residuals in an ARMA model. In the final step, numbers of ARMA models are fitted using these estimated residuals. For instance, if an ARMA (2, 1) is fitted, the regression is:

$$y_t = m + \alpha_1 y_{t-1} + \alpha_2 y_{t-2} + e_t + \beta_1 e_{t-1} + error \tag{14}$$

Such regressions are fitted by OLS for various values of p and q. The residual variance is abstained and the specification chosen that has the lowest value of the Schwarz criterion (SC).

In order to calculate forecasting accuracy, the estimated results are evaluated by three different statistical methods: Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE).

$$RMSE = \sqrt{\sum_{i=1}^{n}(P_i - A_i)^2 / n} \tag{15}$$

$$MAE = \sum_{i=1}^{n}\left|P_i - A_i\right| / n$$

$$MAPE = \sum_{i=1}^{n}\left|(P_i - A_i)/A_i\right| / n * 100$$

That P and *A* represented to the prediction and actual values and n is the number of data. Lewis (1982) has offered a criterion such as table 2 for MAPE:

Table 2. MAPE for model evaluation

MAPE (%)	Forecasting Power
>50	Weak and inaccurate forecasting
20 – 50	Reasonable forecasting
10 - 20	Good forecasting
<10	Highly accurate forecasting

Source: Lewis (1982)

In the next section (Empirical Results), we predicted CO_2 emissions in Iran by using 3 models: GM (1, 1), ARIMA obtained by Hannan - Rissanen and Box- Jenkins methods.

4. Empirical Results

First, to examine stationarity of CO_2 emissions, Augmented Dickey- Fuller[1] test (1981) is used. According to Table 3, the results indicate that this variable is non-stationary in level but it will be stationary by one difference at the 5% Confidence level.

Table 3. The unit root test using of Augmented Dickey- Fuller test (ADF)

Result	Critical value of ADF	The test statistic	
Stationary	-3.51	0.3	**Co_2**
Non- Stationary	-5.51	-5.62	**dCO_2**[2]

Also, using Hannan - Rissanen the degrees of Autoregressive (AR) and Moving Average (MA) were determined. In the first stage the degrees of 8, 9 and 10 AR models are estimated. According to Akaike information criterion (AIC) in Table 4 AR (10) is the most appropriate value.

Table 4. Determining the optimal degree for residuals

Degree of AR	Akaike information criterion (AIC)
AR(8)	8.13
AR(9)	8.23
AR(10)	**8.12**

Then, using AR (10) process, the ARMA (1, 1), ARMA (2, 1), ARMA (1, 2) and ARMA (2, 2) are made. The Schwarz criterions (SC) are shown in table 5.

Table 5. Determining the degree of ARMA

Degree of ARMA	Schwarz criterions (SC)
ARMA (1, 1)	7.272
ARMA (2, 1)	7.265
ARMA (1, 2)	**7.147**
ARMA (2, 2)	7.177

According to table 5, this is obvious that ARMA (1, 2) model is better than another estimated processes. Then, for testing White noise condition, this model has been examined. Based on ADF criterion the obtained value is "-7.607". Therefore, it shows that the residuals are stationary. So the appropriate model is ARIMA (1, 1, 2).

For prediction of CO_2 emissions by using GM (1, 1), we used Matlab software that its codes are placed in Appendix. The results of Carbon Dioxide prediction during 2010-2020 is shown in table 6.

Table 6. The prediction carbon dioxide emissions in Iran during 2010-2020 (million tons)

year	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
GM(1,1)	558.4	588.3	617.5	648.2	680.7	715.1	751.5	790.2	831.4	876.5	925.7
$ARIMA^{B-J}(1,1,2)$	534.7	562.9	592.7	623.9	656.8	691.3	727.7	765.9	806.2	845.5	893
$ARIMA^{H-R}(1,1,2)$	588.9	618.3	649.1	681.3	715.1	750.4	787.5	826.3	866.9	909.6	954.2

After the Forecasting carbon dioxide emissions by GM (1, 1), in order to verify the accuracy of Prediction, RMSE, MAE and MAPE metrics have been used. As shown in the table [7]; the prediction accuracy of GM (1, 1) model is better than both Hannan - Rissanen and Box – Jenkins models. Because, it shows the lowest error rate between metrics. The MAPE metrics are less than 10% in all three models; so the Forecasting power of expression are high in all of them.

[1] . ADF

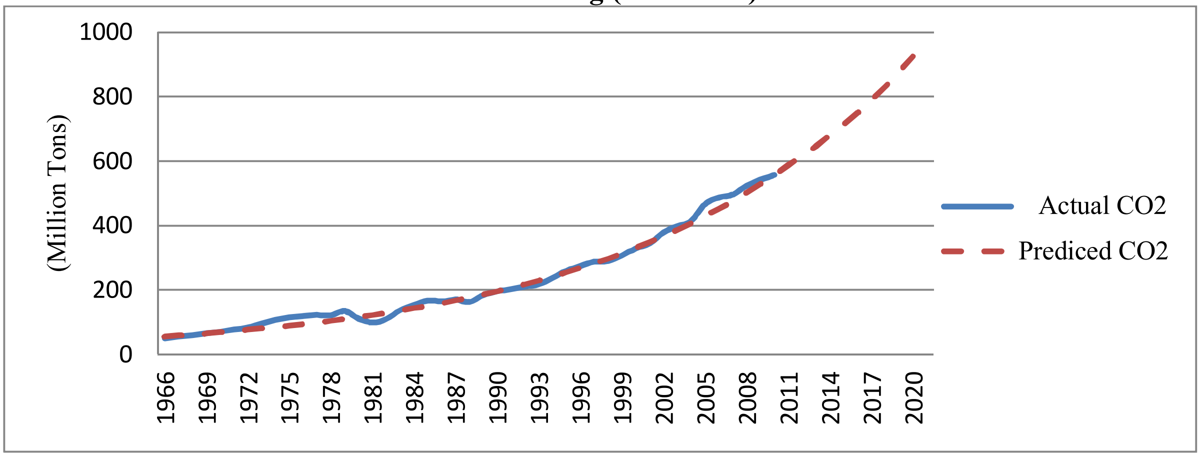
[2] . The first difference of CO_2

Table 7. The accuracy of forecasting models

Metrics \ The prediction models	GM (1, 1)	$ARIMA^{H-R}$(1,1,2)	$ARIMA^{B-J}$(1,1,2)
RMSE	**14.482**	20.06	21.79
MAE	**10.84**	17.35	17.08
MAPE	**6.768**	9.36	9.36

After identifying the best forecasting criterion which represents the ability to forecast GM (1, 1) compared to Box - Jenkins and Hannan – Rissanen, the prediction of carbon dioxide emissions is shown by Grey models until 2020 in figure 2.

Figure 2. The trend of actual and predicted CO_2 emissions in Iran by using GM (1, 1) during (1966-2020)



5. Conclusion

In this study, we tried to predict CO_2 emissions in Iran based on Grey system and Autoregressive Integrated Moving Average and compared the RMSE, MAE and MAPE metrics models. According to the results and determining optimal degree of Hannan – Rissanen and Box - Jenkins for ARIMA were obtained ARIMA (1, 1, 2) model. Although MAPE metrics were obtained less than 10% for three models that shows the accuracy of forecasting them, more accuracy of prediction based on grey system confirmed. Also based on the GM (1, 1) estimated results, the amount of carbon dioxide emissions will reach up to 925.68 million tons in 2020 which shows an increase of 66 percent growth compared to that in 2010.

Due to increasing of CO_2 emissions as an air pollutant, sustainable development will face with a serious threat during the coming years and irreparable damage are enforced to the humans and environment. So, necessary policies and actions in the field of control and reduction of the amount of this gas should be done. So, it is recommended that the government try to improve and reduce pollution by adopting the policies such as collecting taxes and determining of pollution emissions permits for each unit. Also, reducing consumption of fossil fuel that is the main source of CO_2 emission has a significant impact on the decrease of polluting emission of CO_2. Hence, improving the energy efficiency, development of energy saving technologies and the using renewable energies can be very helpful in this regard. Education, promotion of the culture and community awareness can be beneficial items to lower the pollution in society.

References

Akay, D., Atak, M. (2007). *Grey prediction with rolling mechanism for electricity demand forecasting of Turkey*. Energy, 32(9), 1670-1675.

Askari, M., Fetanat, A. (2011). *Long-term load forecasting in power system: Grey system prediction-based models*. Journal of Applied Sciences, 11, 3034-3038.

Ayres, R.U., Nair, I. (1984). *Thermodynamics and economics*. Physics Today, Carnegie–Mellon University, Pittsburgh. 37, 62.

Berndt, B.C. (1988). *Ramanujan's notebooks* (Vol. 2): springer.

Bianco, V., Manca, O., Nardini, S., Minea, A. A. (2010). *Analysis and forecasting of nonresidential electricity consumption in Romania*. Applied Energy, 87(11), 3584-3590.

Box, G., Jenkins, G. (1976). *Time Series Analysis: Forecasting and Control*. Francisco Holden-Day.

Cao, L, J., Tay, F. H. (2003). *Support vector machine with adaptive parameters in financial time series forecasting*. Neural Networks, IEEE Transactions on, 14(6), 1506-1518.

Chang, S. C., Lai, H. C., Yu, H. (2005). *A variable P value rolling Grey forecasting model for Taiwan semiconductor industry production*. Technological Forecasting and Social Change, 72(5), 623-640.

Deng, J.L. (1982). *Control problems of grey systems*. Systems & Control Letters, 1(5), 288-294.

Deng, J.L. (1989). *Introduction to grey system theory*. The Journal of Grey System, 1(1), 1-24.

Guo, Z., Song, X., Ye, J. (2005). *A Verhulst model on time series error corrected for port throughput forecasting*. Journal of the Eastern Asia Society for Transportation Studies, 6, 881-891.

Hannan, E.J., Rissanen, J. (1982). *Recursive estimation of mixed autoregressive-moving average order*. Biometrika, 69(1), 81-94.

Hsu, L.C. (2003). *Applying the grey prediction model to the global integrated circuit industry*. Technological Forecasting and Social Change, 70(6), 563-574.

Huang, C.L., Tsai, C. Y. (2009). *A hybrid SOFM-SVR with a filter-based feature selection for stock market forecasting*. Expert Systems with Applications, 36(2), 1529-1539.

Huang, K.Y., Jane, C.J. (2009). *A hybrid model for stock market forecasting and portfolio selection based on ARX, grey system and RS theories*. Expert Systems with Applications, 36(3), 5387-5392.

Hussain, A. J., Knowles, A., Lisboa, P. J., El-Deredy, W. (2008). *Financial time series prediction using polynomial pipelined neural networks*. Expert Systems with Applications, 35(3), 1186-1199.

Jiang, Y., Yao, Y., Deng, S., Ma, Z. (2004). *Applying grey forecasting to predicting the operating energy performance of air cooled water chillers*. International Journal of Refrigeration, 27(4), 385-392.

Kayacan, E., Ulutas, B., Kaynak, O. (2010). *Grey system theory-based models in time series prediction*. Expert Systems with Applications, 37(2), 1784-1789.

Kim, G., Yun, R.S. (2012). *A Hybrid Forecast of Exchange Rate based on Discrete Grey-Markov and Grey Neural Network Model*. arXiv preprint arXiv:1207.2254.

Kung, C.Y. (2005). *Scheduling the criteria for outsourcing performance by grey decision-making method–a case study of electronic industry in Taiwan*. Journal of Applied Sciences, 5(6), 1022-1026.

Lewis, C.D. (1982). *Industrial and business forecasting methods: a practical guide to exponential smoothing and curve fitting*. Butterworth Scientific London, UK.

Li, G., Wang, T. (2011). *A new model for information fusion based on grey theory*. Inform. Technol. J, 10, 189-194.

Lin, C.T., Yang, S. Y. (2003). *Forecast of the output value of Taiwan's opto-electronics industry using the grey forecasting model*. Technological Forecasting and Social Change, 70(2), 177-186.

Lin, Y., Liu, S. (2004). *A historical introduction to grey systems theory.* Paper presented at the Systems, Man and Cybernetics, IEEE International Conference on.

Lin, S.J., Lu, I.J., Lewis, C. (2007). *Grey relation performance correlations among economics, energy use and carbon dioxide emission in Taiwan*. Energy Policy, 35(3), 1948-1955.

Mao, M., Chirwa, E.C. (2006). *Application of grey model GM (1, 1) to vehicle fatality risk estimation*. Technological Forecasting & Social Change 73:588–605.

Pao, H.T., Tsai, C.M. (2011). *Modeling and forecasting the CO_2 emissions, energy consumption, and economic growth in Brazil*. Energy , *36*(5), 2450-2458.

Tan, C. L., Lu, B. F.(1996). *Grey markov chain forecasting model*. Paper presented at the Proceedings of the First National Conference on Grey Theory and Applications.

Tseng, F.M., Yu, H.C., Tzeng, G.H. (2001). *Applied hybrid grey model to forecast seasonal time series*. Technological Forecasting and Social Change, 67(2), 291-302.

Tien, T.L. (2012). A *research on the grey prediction model GM (1, n)*. Mathematics and computation; 218:4903- 4916.

Wang, Y.F. (2002). *Predicting stock price using fuzzy grey prediction system*. Expert Systems with Applications, 22(1), 33-38.

Wang, X., Chen, Z., Yang, C., Chen, Y. (1999). *Grey predicting theory and application of energy consumption of building heat – moisture system*. Build Environ, 34(4): 417-20.

World Bank. (2007). *The Little Green Data Book*. Washington, DC. 20433 U.S.A.

World Bank. (2013). *The Little Green Data Book*. Washington, DC. 20433 U.S.A.

Wu, Z.Y. (2012). *Stock Index Prediction Based on Grey Theory, Arima Model and Wavelet Methods*. Concordia University.