Energy 116 (2016) 1031–1038

Contents lists available at ScienceDirect

Energy

journal homepage: www.elsevier.com/locate/energy

Application of ARIMA for forecasting energy consumption and GHG emission: A case study of an Indian pig iron manufacturing organization

Parag Sen [a,*], Mousumi Roy [b], Parimal Pal [a]

[a] Department of Chemical Engineering, National Institute of Technology, Durgapur, 713209, India
[b] Department of Management Studies, National Institute of Technology, Durgapur, 713209, India

A R T I C L E I N F O

Article history:
Received 2 November 2014
Received in revised form
16 October 2016
Accepted 19 October 2016

Keywords:
Environmentally conscious manufacturing programs
ARIMA
Forecasting
Energy consumption
GHG emission
Pig iron manufacturing

A B S T R A C T

Environmentally conscious manufacturing (ECM) has become an important strategy and proactive approach for the iron and steel sector of India to produce environment friendly and to reduce manufacturing cost. There are several environmentally conscious manufacturing indicators to evaluate ECM programs. Among those indicators, energy consumption and greenhouse (GHG) emission may be considered critical environmentally conscious manufacturing indicators (CECMI) for Indian iron and steel sector. This paper focuses on forecasting energy consumption and GHG emission for a pig iron manufacturing organization of India because the managers are interested to know the current and future trends of these indicators for better environmental policy. For forecasting purpose, autoregressive integrated moving average (ARIMA) is applied to reveal that ARIMA (1,0,0) × (0,1,1) is the best fitted model for energy consumption. Regarding GHG emission, ARIMA (0,1,4) × (0,1,1) is the best fitted model. In both cases, the forecasts resemble those of the seasonal random trend model, however they appear smoother because the seasonal pattern and the trend are efficiently averaged for energy consumption and as well as GHG emission. Selection of the correct ARIMA models for these indicators will help in accurate forecasting in order to achieve better environmental management practice.

1. Introduction

The importance of the environmentally conscious manufacturing (ECM) programs has been rising at the international level in recent years to prevent global warming and climate change [1]. As manufacturing plays an indispensible role within the global economy, ECM programs may be considered as global agenda to enhance green image [2]. ECM is an economically driven, system-level integrated approach basically to reduce energy consumption and GHG emission [3]. ECM programs enable green manufacturing which is recognized a key strategy for sustainable development of the manufacturing enterprises [4]. The concept may incorporate several strategies among which energy conservation and greenhouse gas (GHG) emission reduction are highlighted by several researchers [5].

In India, industrial sectors use fossil fuels like coal, petroleum and natural gas to emit a significant amount of GHGs among all end-use sectors. The pressure to minimize carbon footprint may become more significant in near future due to the increasing price of energy, increasing demand of energy and the regulations imposed by the government [6]. While using the available energy more efficiently is an appropriate decision to increasing energy demands and unsecure energy supplies, adoption of modern emerging pollution control technologies may control GHG emission [7]. In order to meet the environmental regulations for selling products, Indian manufacturing firms implement strategies to voluntarily reduce the environmental impacts of their products [8]. In order to assess the life cycle of the manufactured products, Indian manufacturers adopt a cradle-to-grave approach (i.e. how much energy is expended or GHG is emitted for unit product manufacturing) rather than just looking at the product or process individually [9]. To minimize the environmental impacts, prediction of the critical environmentally conscious manufacturing indicators (CECMI) is essential [10]. Different types of mathematical modelling have been proposed by the researchers for forecasting different CECMIs like energy consumption and GHG emission [11].

* Corresponding author.
E-mail address: paragbelurmath@gmail.com (P. Sen).

http://dx.doi.org/10.1016/j.energy.2016.10.068
0360-5442/

Prediction of energy consumption and GHG emission help manufacturing organizations by making better environmental management system because proper precautions may be taken in advance to improve environmental performance [12].

Among all the manufacturing sectors, iron and steel sector largely affects the environment as it consumes significant energy to discharge several GHGs in the atmosphere [13]. In case of iron and steel manufacturing, even more than half of the input mass is converted into outputs in the form of exhaust gases, wastes and different by-products. Since iron and steel industry is one of the most energy intensive industries, it accounts a significant amount of percentage of total global emissions [14]. Iron and steel industries in India also produce massive amount of wastes [15]. Solid wastes can be recycled to reduce the consumption of raw materials; however energy consumption and GHG emission are two unavoidable parameters that significantly affect the environment. Hence, energy consumption and GHG emission may be considered CECMIs for the iron and steel sector. These two parameters are also considered by several researchers while dealing with the environmental problems of iron and steel sector [16]. Prediction of energy consumption and GHG emission may benefit these industries to take proper initiatives to control energy consumption and GHG emission in advance. However, accurate prediction is possible when correct forecasting method is chosen [17].

This paper implements autoregressive integrated moving average (ARIMA) model to forecast energy consumption and GHG emission due to its richer information on time related changes than the other similar methods like moving average, multiple regression models, exponential smoothing and neural network [18]. It is very popular in the field of forecasting energy consumption and GHG emission because of its flexibility and orderly searching at each stage (identification, estimation and diagnostic check) for an appropriate model [19]. In the current research work, monthly energy consumption and GHG emission data of an Indian pig iron manufacturing organization (a process industry where there is no concept of unit manufacturing) are used as input data for the ARIMA model. This paper also discusses the usefulness and limitations of ARIMA model for forecasting purpose. Information about rest of the paper is organized as follows. Literature review is discussed in Section 2. Study methodology is provided in Section 3. Results and discussion is illustrated in Section 4. Finally, the conclusion section is described in Section 5.

2. Literature review

Several researchers have highlighted the importance of energy and GHG emission modeling [20,21]. Many of them choose ARIMA for time series modelling of energy consumption and GHG emission so that these indicators may be predicted in advance. In case of time series data, ARIMA has the advantage over the other similar methods by determining the proper model to best fit the respective time series. For normal and uncorrelated conditions ARIMA model has a constant mean and the fluctuation may take place around the mean. If the observations are correlated, then the correlation nature and mean drift are illustrated by either deterministic or stochastic disturbances. Deterministic disturbances are characterized by step shifts in the process mean. However, stochastic disturbances are random in nature and might be stationary (if process observations vary around a fixed mean with a constant variance) or non-stationary (if process observations do not vary around a fixed mean and do not have a constant variance). Stochastic difference equation can be used to forecast one-step-ahead disturbances by choosing ARIMA as highlighted by the researchers [22].

Ediger and Akar implement ARIMA to forecast primary energy demand of different fuels in Turkey to recommend the nature of energy policy [23]. While Liu et al. apply ARIMA to save energy in information collection [24], Mohamed and Bodger implement ARIMA to forecast electricity consumption in New Zealand using economic and demographic variables [25]. Abdel-Aal and Al-Garni forecast monthly electric energy consumption in the eastern part of Saudi Arabia [26]. Saab et al. also consider ARIMA to model and forecast electricity consumption as it is the major source of energy in Lebanon [27]. Albayrak forecast primary energy production and consumption in Turkey for a long time period using ARIMA [28]. Yeboah et al. perform a literature survey regarding forecasting aggregate and disaggregate energy consumption using ARIMA models. These literature actually address the advantage of implementing ARIMA in energy forecasting through the consideration of autoregressive and moving average models simultaneously. Hence, they can control the noise elements and seasonality effectively for more accurate prediction of energy consumption compared to only autoregressive or only moving average models [22].

GHG emission forecasting is another important dimension which may use ARIMA as has been addressed by different researchers [29]. GHGs of iron and steel sector include carbon dioxide (CO_2), sulpher oxides (SO_x) and nitrogen oxides (NO_x). While SO_x constitutes of all sulpher oxides including sulpher dioxide (SO_2) and sulpher trioxide (SO_3), NO_x refers to all oxides of nitrogen except nitrous oxide (N_2O). Carbon monoxide also may be considered as a GHG for iron and steel sector as it has a global warming potential (GWP) around 7 considering a time horizon of 20 years [30]. Ang et al. apply ARIMA to project CO_2 emissions in Malaysia [31]. Silva also integrates ARIMA to forecast for energy-related CO_2 emissions in the United States [32]. Liu et al. apply ARIMA and focus on the essence to reduce GHG emission for China [33]. Lotfalipour et al. predict CO_2 emissions in Iran using ARIMA model [34]. However, modelling of SO_x and NO_x has not been proposed by the researchers and practitioners as these GHGs have negative GWPs and may vary highly as per regions [35].

Though most of the researchers prefer ARIMA to forecast, the limitations of ARIMA are also pointed out. The most important limitation of ARIMA is that it requires a long data series. Most of the researchers propose at least 50 observations for an ARIMA model which may not be possible very often. Some researchers find that regression model provides higher efficiency to forecast GHG emission as compared to ARIMA model in case of small sample size [36]. Apart from these factors, the forecasting objective is another important condition which must be taken care of. It is found that ARIMA is quite suitable for short term forecasting rather than long term forecasting. However, if long data series is available and the objective is short term forecasting, ARIMA has become successful to accurately forecast energy consumption and GHG emission. Previous research works do not focus on short term forecasting of energy consumption and GHG emission for a specific manufacturing organization, creating a research gap. Hence, how to select the best ARIMA model to forecast energy consumption and GHG emission for a particular manufacturing organization may be considered an area of research. The novelty of the current research work lies in its methodology and managerial implications. Energy managers look for short term forecasting because almost every year energy and pollution control technology is upgraded for continuous improvement. This research work helps the energy managers to identify the best possible ARIMA model for short term forecasting.

3. Study methodology

In this section, study methodology of ARIMA is described. This study methodology is a systematic way to choose the best possible ARIMA models for forecasting. ARIMA models are univariate as they use only the history of the time series in order to express how the