WAREHOUSE PERFORMANCE PREDICTION MODEL USING PARTICLE SWARM OPTIMIZATION-BASED GREY THEORY

BY

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CERTIFICATE OF APPROVAL

The thesis titled **"WAREHOUSE PERFORMANCE PREDICTION MODEL USING PARTICLE SWARM OPTIMIZATION-BASED GREY THEORY"** submitted by Md. Rakibul Islam, Student No: 1015082003, Session: October 2015, has been accepted as satisfactory in partial fulfillment of the requirements for the degree of Master of Science in Industrial and Production Engineering on 14 September 2020.

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ABSTRACT

Warehouses are one of the key components in the supply chain of a firm. An improvement to the operational efficiency and the productivity of warehouses, is crucial for supply chain practitioners and industrial managers. Overall warehouse efficiency largely depends on synergic performance. The managers pre-emptively estimate the overall warehouse performance, which requires an accurate prediction of a warehouse's key performance indicators (KPIs). This research aims to predict the KPIs of a ready-made garment (RMG) warehouse in Bangladesh with low forecasting error in order to precisely measure the overall warehouse performance. Incorporating advice from experts, conducting a literature review, and accepting the limitations of data availability, this study identifies 16 KPIs. Traditionally, the grey method (GM), GM (1, 1) is used in the literature to estimate the grey data with limited historical information but not absolute. To reduce the limitations of GM (1, 1), this study presents a novel Particle Swarm Optimization (PSO)-based integrated grey model called PSOGM (1, 1) to predict the warehouse's KPIs with less forecasting error. This study also uses the genetic algorithm (GA)-based grey model, GAGM (1, 1), discrete grey model, DGM (1, 1) to assess the performance of the proposed model in terms of the mean absolute percentage error (MAPE). The proposed model outperforms the existing grey models by reducing the MAPE 6-29% for the KPIs of three distinct warehouses, and 23-28% for the pilot data series and, in turn, leads to estimate the overall warehouse performance through the forecasting of the KPIs. To find out the optimal parameters of the PSO and GA algorithms before combining them with the grey model, this study adopts the Taguchi design method. Finally, this study aims to help warehouse professionals make overall warehouse performance estimations in advance to take control measures regarding warehouse productivity and efficiency.

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LIST OF ABBREVIATIONS

AHP	: Analytic Hierarchy Process
ANN	: Artificial Neural Network
DGM	: Discrete Grey Model
DNE	: Derived Non-Equigap
FGM	: First Entry Grey Model
GA	: Genetic Algorithm
GM	: Grey Model
GAGM	: Genetic Algorithm based Grey Model
IRGM	: Improved-Response Grey Model
KPI	: Key Performance Indicator
MAD	: Mean Absolute Deviation
MAE	: Mean Absolute Error
MAPE	: Mean Absolute Percentage Error
MFO	: Moth-Flame Optimization
MSE	: Mean Square Error
PSO	: Particle Swarm Optimization
PSOGM	: Particle Swarm Optimization based Grey Model
RMSE	: Root Mean Square Error
SGM	: Seasonal Grey Model
TIC	: Theil's Inequality Coefficients

CHAPTER 1
INTRODUCTION

1.1 Overview

Performance is an achievement of a given task measured against a predetermined known standard (Rahman et al., 2019). It is one of the critical elements for managers in various fields to manage their jobs. Technically, it can be a helpful tool for them to predict or measure the overall efficiency of the organization parallel to its strategy. Efficiency can also assist the industrial managers in taking corrective action in advance for the systems at the organization's risk. Therefore, there are multiple ways and matrices used by the managers for measuring the performance of an organization. From another point of view, performance prediction is another crucial matter in the sense of the accuracy of the forecasting as studied by many researchers recently. Supply chain performance measurement and prediction are widespread at present days as it is being complexed day by day. However, warehousing is an essential component of logistics operations, contributing to the supply chain speed and profit. The success of managing the warehouse in real scales depends on the measurement of key performance indicators (KPIs) (Krauth & Moonen, 2005). A KPI is a quantifiable metric that helps a company, an expert, or worker assess their accomplishment relative to their goals.

While this research topic is active, there are only a few studies in the literature on predicting warehouse performance through forecasted KPI values. Some scholars guide the ways to find out the KPIs and the matrices related to the warehouse management (Johnson & McGinnis, 2011; Krauth, et al., 2005; Kusrini, Novendri, & Helia, 2018). Regarding the time, managers are getting concerned about the performance of the warehouse. At the same time, there have developed many matrices and KPIs to calculate the efficiency of the warehouses. Different warehouses need different kinds of methods and KPIs to evaluate their output. But, managing the warehouses successfully and measuring and predicting its performance is a challengeable issue requiring to overcome two crucial things: the selection of the right KPIs and prediction of the KPIs values based on time series data, accurately. This study, however, comprehensively addresses the difficulties related to performance prediction based on forecasting KPIs through the use of historical grey data. Accordingly, the challenge is rooted in uncertainty and unavailability. Considering this problem, the grey theory is a non-traditional forecasting methodology focused on incomplete, ambiguous, scant, and fuzzy information. This theory was offered by Deng (1982), which is an excellent choice to define future trends for data from a time series.

The grey system theory is reasonably appropriate for forecasting future data with less prediction error. It is a widely used and established forecasting model for predicting grey type data as well as dealing with uncertainty in data. It interacts with unknown structures that comprise the information partly understood by the creating, exploring, and extracting from the available data. Uncertain structures with small samples and insufficient knowledge are commonly found in nature. This fact determines the broad applicability of the theory of grey systems (Liu et al., 2016). Traditional grey forecasting model, i.e., GM (1,1) is not error-free in predicting the time sequence data in many ways. Accuracy is a crucial matter in forecasting and accordingly, researchers are devoted to minimizing it. Concerning the development time to the current time, the traditional grey model is enriched by many researchers and various improved models of GM (1,1) have been established (Hsu & Chen, 2003; Madhi & Mohamed, 2016).

Optimization of a grey system is also an active topic and interesting. The parameter optimization of the grey forecasting model can produce a better-predicted result than the traditional grey method. Cao et al. (2014), Hu and Jiang (2017), Lai et al. (2015), Li and Wang (2018), Wang et al. (2009) have showed some studies on the parameter enhancement of the traditional grey method and compared the optimized grey model result with the GM (1,1) prediction model. They conclude the predicted outcome of the improved model is better than the existing model. For more accuracy, this improvement is going on today, and the evolutionary algorithms are an alternative answer. To improve on the parameter optimization of the GM (1, 1) model, the particle swarm optimization (PSO) algorithm is one of the standard algorithms used in a variety of optimization problems (Kennedy & Eberhart, 1994; Fukuyama, 2007; Parsopoulos & Vrahatis, 2010; Bansal, El-Shorbagy & Hassanien, 2018).

Taken together, the current research intends to develop an integrated PSO-based grey forecasting model, namely PSOGM (1,1), to increase the forecasting accuracy by controlling the background parameters associated with the single variable grey method, i.e., GM (1,1). After selecting the right KPIs for the warehouse of a garments industry in Bangladesh, the proposed grey model is employed to predict the values of the KPIs of that warehouse for the managers to predict the overall warehouse performance. The warehouse experts give the weight of the selected KPIs to prioritize their effect on the overall performance. The integrated model as a methodological contribution in the warehousing industry domain may help warehouse managers to design, plan, and to manage operations of a warehouse successfully.

1.2 Objectives of the Study

The specific objectives of this research are:

(i) To formulate a PSO-based integrated grey prediction model, PSOGM (1, 1) to minimize the predicting errors of time series data for single variables.

(ii) To calculate warehouse performance by predicting the values of the KPIs with the help of the developed prediction model.

In conclusion, the proposed research develops a framework to predict the overall performance of a warehouse by the output of PSO based grey prediction method, which incorporates the KPIs for a warehouse. This proposed framework could improve warehouse performance and, in turn, enhance enterprises' supply chain efficiency.

1.3 Organization of the Thesis

This thesis has been organized into seven separate chapters, along with a list of references and appendices. They are described as follows:

Chapter 1 is entitled "INTRODUCTION," which describes the motivation and background of this research for developing a hybrid grey forecasting method based on the PSO algorithm to minimize the forecasting errors by optimizing the parameters of the GM (1,1) model. This chapter also describes the applications of the proposed PSO based grey forecasting model. The research objectives and the outline of the methodology followed in this thesis are also depicted there.

Theoretical background on the traditional grey prediction model, GM (1,1), has been discussed in Chapter 2, titled "LITERATURE REVIEW." Previous studies in focusing on improvement of the GM (1,1) model and the application of GM (1,1) model in various forecasting researches are briefly discussed in this chapter. A review of the significant KPIs for warehouses and their uses to measure the performance of a warehouse is also presented in Chapter 2.

Chapter 3 explains the theoretical framework for the algorithms and models used for conducting this research. In this chapter, the PSO algorithm, and the original grey model, GM (1,1) are discussed clearly with illustration and flowchart. A numerical example is also given here both for the PSO and GM (1,1) model to clarify the algorithms. Additionally, a brief description of the GA and variant of the GM (1, 1) model, the DGM (1, 1) model, are also placed here. In chapter 4, includes the details methodology followed for conducting this research. The procedures are summarized in a flowchart that represents the research framework. Besides, this chapter discusses the PSO based-GM (1,1) model and identifies the primary warehouse related KPIs with their description. Also, this chapter describes the parameter design using the Taguchi method of the optimized algorithms and comparison of the performance of the proposed model with other grey models.

Chapter 5, which is called "IMPLEMENTATION OF PROPOSED MODEL," explains a case study on the prediction of the overall performance of a warehouse of an RMG industry using KPIs. The details of the data collections and the processing of the data for the selected KPIs of the warehouse is presented in this chapter. Here, the ranking of the KPIs is done by the AHP method. Additionally, this section deals with a comparison of the simulation results obtained PSOGM (1,1) forecasting and other grey models based on the MAPE.

Chapter 6, termed as "CONCLUSIONS & RECOMMENDATION," discusses the different results and findings from the improved prediction model as well as from the original forecasting model. Additionally, an implication of performance measurement of the garments-warehouse is depicted in this chapter. Finally, the scope for future research is also recommended here.

The “REFERENCES” added after the description of the main thesis enlists all the relevant references used in this research. At the end of this thesis includes an “APPENDICES” that gives a MATLAB code for the proposed grey prediction model, the PSOGM (1,1) forecasting model. The “APPENDICES” also includes the data collection table for the KPIs of the warehouse of the Best Shirt Ltd. and the pairwise comparison matrix o that selected KPIs.

CHAPTER 2
LITERATURE REVIEW

This chapter provides a review of the current state and background of the research of two key areas of this study. It gives a picture of the recent research and the background study of the traditional grey prediction model and its improvements in the time series data prediction. It also delineates the review of the use of the PSO algorithm into a grey model to increase its prediction accuracy. An analysis of the background research on warehouse performance measurement using KPIs is another crucial part of this chapter.

2.1 Grey Prediction Model, GM (1, 1) and its Improvement

The prediction method based on time series involves moving average and exponential smoothing (Gooijer & Hyndman, 2006), neural networks (Tealab, 2018), and grey models (Kayacan et al., 2010; Liu et al., 2011). The applicability of exponential smoothing and a moving average is limited to linear time series data. The artificial neural network (ANN) approach has performed excellently with both linear and nonlinear time series data. However, for higher accuracy, it requires a large quantity of data to train the system. The grey model, which too can be implemented with both linear and nonlinear data, does not require as large of a sample for accurate prediction.

There are two categories of uncertainty: stochastic and fuzzy. Probabilistic statistics are used to analyze stochastic uncertainty where a large amount of historical data is required. On the other hand, the mathematics of fuzzy or the theory of the grey systems are used to analyze fuzzy uncertainty with less information (Liu et al., 2016). Through this method, the operational characteristics of systems and their evolutionary laws can be correctly described and tracked with success (Liu et al., 2016). There are commonly indeterminate processes with limited samples and scant data in the real world, which is why the theory of gray systems is widely applicable (Cui et al., 2013; Liu et al., 2011).

GM (1,1) forecasting model is one of the central models in the theory of the grey system commonly used in the analysis of time-series data (Kayacan et al., 2010). Grey forecasting includes sequence forecasting, calamity forecasting, prediction of seasonal calamities, topological forecasting, and systematic forecasting (Lü & Lu, 2012). One of the grey system theory's most significant features is the use of accumulated generation operation (AGO) to minimize data randomness (Zeng et al., 2020). The AGO approach eliminates noise efficiently by transforming random time series data into a monotonously increasing sequence, which can rapidly evaluate systematic regularity (Liu et al., 2016; Madhi & Mohamed, 2016).

Due to the simplicity of the GM (1, 1) model and its potential for predicting time series data, many researchers have used this model. It has been successfully used in climate (Dengiz et al., 2019), energy (Deng & Dong, 2019; Li & Zhang, 2019; Lu, 2019; Zhang et al., 2019), healthcare performance (Rahman et al., 2019), industrial technology and safety (Lü & Lu, 2012), petroleum exploration (Wang & Song, 2019), among others. Hui et al. (2009) used the GM (1,1) model to forecast the growth of larches and tested the precision of the model. Li et al. (2016) used the grey model in the early warning system for predicting the incidents of iron and steel concerning the prevention of the accident and management of the hazard. The GM (1, 1) model was also used to determine the number of fixture locations in sheet metal operation (Yang et al., 2017), for breast cancer prediction (Iqelan, 2017), and to predict the selected countries' research output (Javed & Liu, 2018).

Although the GM (1, 1) model has shown promise in various fields, its predictive results may sometimes be unreliable; thus, researchers have proposed various improvements through parameter and structure optimization (Zeng et al., 2020). Hsu and Chen (2003) suggested an enhanced grey GM (1,1) model combining the residual adjustment and ANN (Artificial Neural Network). To enhance the predictive performance of the grey predicting model, Tien (2009) modified the GM (1, 1) model concerning the effect of the first entry of the original series and proposed a new grey model, GM (1, 1). Cui et al. (2013) put forward a novel grey forecasting model and its optimized model called the NGM (1, 1) model.

Based on the error analysis of the GM (1,1) model, Wang et al. (2009) proposed a new approach for optimizing background value in model GM (1,1) using the discrete function with non-homogeneous exponential law to match the accumulated series. Lee and Tong (2011) proposed a GM (1, 1) model that combines a genetic algorithm (GA) for the parameter optimization of the GM (1, 1) model. Cao et al. (2014) and Ying et al. (2015) also developed a grey forecasting model with a background optimization technique combining with the method of optimizing the initial item. To enhance the simulation and prediction precision of the traditional GM (1, 1) model, Lai et al. (2015) proposed an upgraded grey prediction method using BP (Back Propagation) neural network. Madhi and Mohamed (2016) paired background value optimization and initial condition optimization (Madhi & Mohamed, 2017) to improve the precision of the GM (1, 1) model.

Hu and Jiang (2017) introduced a GM (1, 1) method that incorporated ANN to increase prediction accuracy. Zhao et al. (2016) proposed a hybrid GM (1, 1) model for the prediction of electricity consumption using a moth-flame optimization (MFO) that optimized the parameters of the model. Aiming at accurate power load forecasting Li and Wang (2018) proposed an annual power load forecasting model using a traditional GM (1,1) prediction model combining the background value optimization (BVO). Ding, Hipel, and Dang (2018) proposed an updated grey using initial condition optimization and rolling mechanism techniques combining with the GM (1,1) model to increase the prediction accuracy. Hao et al. (2018) offered GM (1, 1) model based on ANN and exponential smoothing to predict vehicles to be recycled at the end-of-life.

Through this review, it is clear that the performance of enhanced grey prediction models exceeds that of the traditional GM (1, 1) model. Of all these cases, the most relevant to this study are those that incorporate initial condition optimization which was only a single parameter optimization. The prediction accuracy of the GM (1, 1) model further depends on the development coefficient, a, and the grey action coefficient, b. Researchers now look to heuristic algorithms using for the optimization of these two development coefficients to improve prediction accuracy of the GM (1, 1) model. This study uses the basic PSO algorithm as the heuristic algorithms to optimize these two development coefficients.

PSO is a population-based heuristic optimization process that simulates social behavior as birds flocking and fish schooling to a favorable location in multidimensional space to achieve specific targets (Fukuyama, 2007; Olsson, 2011; Parsopoulos & Vrahatis, 2010). Getting the inspiration from the population of nature like the swarms of birds and fish schooling, Kennedy & Eberhart (1994) first developed the PSO algorithm. The basic principles of the PSO process have been studied from the following researches. Zhang, Wang, and Ji (2015) presented a detailed investigation of the PSO algorithm. Couceiro and Ghamisi (2015) explained the core mechanisms behind the conventional PSO and discussed its advantages and disadvantages. El-Shorbagy and Hassanien (2018) offered an extensive review of PSO, development, and fundamental concepts of PSO. Wang et al. (2018) presented the origin of the PSO algorithm and stated the background and theoretical analysis of it. In the book, 'Evolutionary and Swarm Intelligence Algorithms,' Bansal et al. (2019) also described the fundamentals of the PSO algorithm.

PSO can achieve faster convergence with fewer parameter settings, and its implementation is far simpler. Since the conception of PSO, it has been used in many fields, such as mechanical processes (Latchoumi et al., 2019), earthquake fault parameter estimation (Wang & Ding, 2020), scheduling (Bekrar et al., 2015), manufacturing process optimization (Bensingh et al., 2019), parameter selection in indoor positioning system (Guo et al., 2019), combining with ANN and regression model for time series forecasting (Pradeepkumar & Ravi, 2017), algorithm performance improvement (Essiet et al., 2018) and so on. However, very few studies have found in literature applying PSO in forecasting, combining with a grey prediction model. Among these scant studies, Zhou et al. (2009) proposed a novel gray forecasting model where PSO was applied in parameter optimization of the nonlinear grey Bernoulli model (NGBM). In that research, they optimized only the output coefficient of background value, p (somewhere used as Alpha, α) and a Bernoulli differential equation parameter, r.

Similar research was performed using the PSO based grey model by Qian et al. (2011) for the prediction of the traffic accident, Ding et al. (2018) for predicting China's electricity consumption, and Ma et al. (2011) to forecast the underground pressure. Ma, Zhu, and Wang (2013) also optimized the output coefficient of background value α (here indicated as λ) using the PSO algorithm into the conventional GM (1,1) model. Wang, Li, and Pei (2018) forecast the electricity consumption of the primary economic sectors using a PSO based grey GM (1,1) model where they used the optimization of the production parameter, α (here indicated as e) of the GM (1,1) model.

Recent research has mainly focused on improving prediction precision by adjusting the background value of the GM (1, 1) model. Li et al. (2016) used the PSO algorithm to optimize the model's development coefficients, a and b of the GM (1, 1) model. They set the range of the coefficient a as $[-0.5, 0.5]$ and the range of b as ($b \in [\min (\mathrm{a} \times x^{(1)} (k-1) + x^{(0)}(k)), \max (\mathrm{a} \times x^{(1)} (k) + x^{(0)}(k))]$, $k = 1,2,3, \ldots, n$), which is actually dependent on the value of a. Xu, Dang, and Gong (2017) proposed a modified GM (1, 1) model introducing with a time response function (TRF) into it and used PSO to optimize the parameter of the TRF. In their study, they used the traditional calculation method to evaluate the value of the development coefficients, a, and b. Meng, Wang, and Li (2017) used PSO to optimize the parameters a and b of the grey model without defining the true range of those parameters. The similar kind of research was performed by Wang and Li (2019) to optimize the structural parameters a and b of the advanced version of the grey forecasting model, derived non-equigap grey Verhulst model (DNE grey Verhulst model).

One of the leading research gaps found in the study by Ervural and Ervural (2018) for energy demand forecasting in Turkey where they used GA and PSO to optimize the development coefficients, a and b in the grey forecasting model. They set the range of a as $[-0.5, 0.5]$ and b as $[b \in \min\left(0.5 \times x^{(0)}(k)\right), \max\left(0.5 \times x^{(0)}(k)\right), k = 1, 2, \ldots, n]$. The limitation of the range of the coefficient, b is when the randomness of historical data series is higher than the value of the coefficient, b goes beyond the limit. Parallelly, with the use of the PSO algorithm into the grey model, few researchers have also been used the GA algorithm to optimize the development coefficients and background value in the grey model (Hu, 2017; Lee & Tong, 2011; Liu & Xie, 2019; Özcan & Tüysüz, 2018; Wang, 2013; Yahya et al., 2020). The application of the improved grey model is tabulated in (Table A1 of Appendix-A).

It is clear that researchers today are more concerned about the optimization of the grey development coefficient to increase the prediction accuracy of the GM (1, 1) model than they are about background value and initial value optimization. No recently published works consider the above-mentioned concerns about the ranges of the grey development coefficients a, and b. This study employs a logical range for the development coefficients that is determined by the mean-generated sequence equation and the least square method of the GM (1, 1) model using the range of the background value α $[0, 1]$. The other important elements have been concerned here are the robustness and the search performance of the optimization algorithm by the Taguchi method (Chen et al., 2016; Fathollahi-Fard & Hajaghaei-Keshteli, 2018; Freddi & Salmon, 2019; Wang et al., 2014).

Therefore, the development of an improved robust PSO based grey model, PSOGM (1, 1) model, is still required to accurately predict grey type time series data and, in turn, yield the scope of this study. This study also develops a tuned GA based GM (1, 1) model to predict the performance of the warehouse.

2.2 Warehouse Performance Measurement

KPIs assess an enterprise's performance relative to its goals, thereby allowing corrective action where anomalies occur. The success of warehouse management largely depends on the measurement of KPIs (Krauth & Moonen, 2005). Metrics is an essential tool for performance measurement in operations management that connects the execution, strategy, and overall value creation. Changing market patterns puts intense demands on conventional metric systems and causes tension between firms and their supply chains. Melnyk, Stewart, and Swink (2004) conveyed the value and significance of research related to functions of metrics, the dissimilarity between metrics, metrics systems, and metrics sets.

There are many KPIs identified in the literature that pertain to warehouse management. Krauth and Moonen (2005) classified the performance indicators in the short-term and long-term metrics. In their research, they further split the KPIs into five categories: Effectiveness, Efficiency, Satisfaction, IT, and Innovation. To find the performance indicators for logistic service, Krauth et al. (2005) published a literature review on several fields related to the performance measurement for logistics and supply chain management, logistics service provider industry, and warehouse management. Johnson and McGinnis (2011) addressed the evaluation methods for warehouse functional performance based on empirical evidence introducing a new methodology and used the process to a large sample of warehouses.

Some studies (Staudt et al. 2015a; Staudt et al., 2015b) have evaluated the efficiency of warehouses by synthesizing the literature on operational warehouse efficiency with interpretations of performance indicators pertaining to time, expense, quality, and productivity. Maté, Trujillo, and Mylopoulos (2017) proposed that decision-makers combine strategic business priorities with quantitative KPIs when assessing warehouse performance. Makaci et al. (2017) presented a pooled warehouse’s sources of uncertainty, risks, and new KPIs. Conducting extensive case studies for the warehouse management system, Chen et al. (2017) developed a model of process performance and then establish KPIs for logistics companies and identify critical warehouse management system functions and processes. They suggest eight KPIs that concentrate on the efficiency, accuracy, cost, security, and timeliness of warehouse management systems based on their established process performance model and the critical functions and processes. Kusrini et al. (2018) and Nurjanah et al. (2018) described 25 KPIs for warehouses based on the Frazelle model (Frazelle, 2016), applying them to various warehouses. They used the analytic hierarchy process (AHP) method to rank the KPIs and stepwise normalization (SNORM) to evaluate the final score regarding the benchmark data on warehouse performance. Wudhikarn, Chakpitak, and Neubert (2018) detailed numerous organizational measures that are frequently applied in studies related to logistics and significantly affect organizational performance.

Based on this review, another aim of this study is to define the most critical KPIs for an RMG industry of Bangladesh. This part of the study uses the Frazelle model as its base model. This model generally divides warehouse KPIs into five main categories: financial, productivity, utilization, quality, and time. In this paper, however, the utilization category is merged with the quality category. In line with this model and the opinions of experts, primarily sixteen major KPIs are selected and placed under one of the four main categories.

The AHP method is applied to measure the KPIs' global weights; this method is widely used in many fields, including the financial sector (Pérez et al., 2017), operational performance (Podgórski, 2015), KPIs ranking (Bhatti & Awan, 2014; Kaganski et al., 2018; Shahin & Mahbod, 2007), supply chain (Anjomshoae et al., 2019), and so on. Finally, the overall warehouse performance is forecasted by using the selected KPIs predicted values obtained from the proposed PSOGM (1, 1) model multiplied with the weight of each KPI derived from the AHP model.

CHAPTER 3
THEORETICAL FRAMEWORK

This chapter explores the theoretical background of the undertaken algorithms applied in this research work. Except for the proposed model, some other established methods are used in this thesis. The grey predicting method, GM (1,1), is used as the fundamental forecasting model for the prediction of time-series data. In contrast, the PSO algorithm is applied as an optimizing algorithm for further improvement of the GM (1,1) model. The working procedures of the PSO algorithm and GM (1,1) model have been described step by step in this chapter. Besides, a numerical example is provided with both for the PSO and GM (1,1) model. Additionally, this chapter also explains the fundamental procedures for the DGM (1, 1) model for simulating the time series data, which will help to compare the forecasting result obtained from the other two models. A brief description of the GA algorithm is provided in this chapter, which is used as a GA based GM (1, 1) model for the comparison. Finally, the AHP methods for measuring the weights of the selected KPIs for the warehouse are also described here.

3.1 Grey Prediction Model, GM (1, 1)

The GM (1, 1) model is the fundamental method of grey system theory. It is popularly referred to as the "first order and single variable grey method." According to (Liu et al., 2016), the GM (1,1) model works in the following steps:

Step 1. The original time series is given as $X^{(0)}$ for the *n* number of non-negative samples (time point), can be expressed as the following way,

$$X^{(0)} = \left[x^{(0)}(1), x^{(0)}(2), \dots, x^{(0)}(n)\right], \qquad n \geq 4 \tag{3.1}$$

The actual data is transformed into monotonically increasing data sequences through the accumulated generating operation (AGO) which attenuates the disorderliness and the noise of the original series data. From the initial data sequences, the incremented data series $X^{(1)} = \left[x^{(1)}(1), x^{(1)}(2), \dots, x^{(1)}(n)\right]$ can be obtained through the AGO operator as follows,

$$x^1(k) = \sum_{i=1}^{k} x^0(i), \qquad k = 1,2,3, \dots \dots, n. \tag{3.2}$$

The new incremented series, $x^{(1)}$ follows an approximate exponential law, and it is a monotonic increase sequence assuming the raw series is smooth enough. Now, from the $X^{(1)}$ Serie the mean generated sequence $Z^{(1)}$ can be calculated as, $Z^{(1)} = \left[z^{(1)}(2), z^{(1)}(3), \dots, z^{(1)}(n)\right]$, where the mean value of the two-adjacent data is the $Z^{(1)}(k)$ and can be determined as,

$$z^{(1)}(k) = \alpha x^{(1)}(k) + (1-\alpha)x^{(1)}(k-1), \qquad k = 2,3, \dots \dots, n. \tag{3.3}$$

Here, the positioned coefficient of the grey number interval is called α. The value of α is generally set as 0.5 for the mean whitenization (imaging), but the value of α can be in the range between [0, 1].

Step 2. The grey first-order differential equation can be established for the predictions of the future trend as follows,

$$x^{(0)}(k) + az^{(1)}(k) = b \tag{3.4}$$

Now the differential equation of the above equation can be expressed as,

$$\frac{dx^{(1)}}{dt} + ax^{(1)} = b \tag{3.5}$$

The parameters a and b are named as the development coefficient and control coefficient, respectively. These two parameters are called the background coefficients of the GM (1, 1) model and can be calculated using the approximation method of the linear regression, as,

$$\hat{a} = \begin{bmatrix} a \\ b \end{bmatrix} = [B^T B]^{-1} B^T\, Y \tag{3.6}$$

Where, $B = \begin{bmatrix} -z^{(1)}(2) & 1 \\ -z^{(1)}(3) & 1 \\ \vdots & \vdots \\ -z^{(1)}(n) & 1 \end{bmatrix}$, and $Y = \begin{bmatrix} x^{(0)}(2) \\ x^{(0)}(3) \\ \vdots \\ x^{(0)}(n) \end{bmatrix}$

Step 3. The grey forecasting formula is constructed using the development coefficients a and b calculated from equation (3.6) as follows,

$$\hat{x}^{(1)}(k) = \left[x^{(0)}(1) - \frac{b}{a}\right] e^{-a(k-1)} + \frac{b}{a} \tag{3.7}$$

Where, the value of $\hat{x}^{(1)}(k)$ implies the forecast of $x^{(1)}(k)$ at time point k with the initial condition is $x^{(1)}(1) = x^{(0)}(1)$. The sequence of inverse accumulated generating operation (IAGO) can be calculated as follows,

$$\hat{x}^{(0)}(k) = \hat{x}^{(1)}(k) - \hat{x}^{(1)}(k-1), \ \ k = 2,3, \dots, n \tag{3.8}$$

Step 4. The error associated with the simulation is analyzed. There are many metrics available to measure the prediction error. Here, MAPE is used to determine the forecasting error:

$$MAPE = \frac{1}{n}\sum_{k=1}^{n} \nabla_k \times 100 \tag{3.9}$$

where n is the total number of the raw data, and $\nabla_k = \frac{|\varepsilon(k)|}{x^{(0)}(k)} = \frac{|x^{(0)}(k) - \hat{x}^{(0)}(k)|}{x^{(0)}(k)}$ is the absolute relative error of the k^{th} raw data. Table 3.1 lists the most widely used precision scale for testing the forecasting models using the MAPE values (Lewis, 1982). The flow chart of the GM (1,1) model based on the above steps is illustrated in Figure 3.1.

Table 3.1: The MAPE (%) scale for determining the accuracy of the forecasting model.

Forecasting Accuracy	**MAPE (%)**
High forecasting accuracy	<10
Good forecasting	10–20
Reasonable forecasting	20–50
Inaccurate prediction	>50

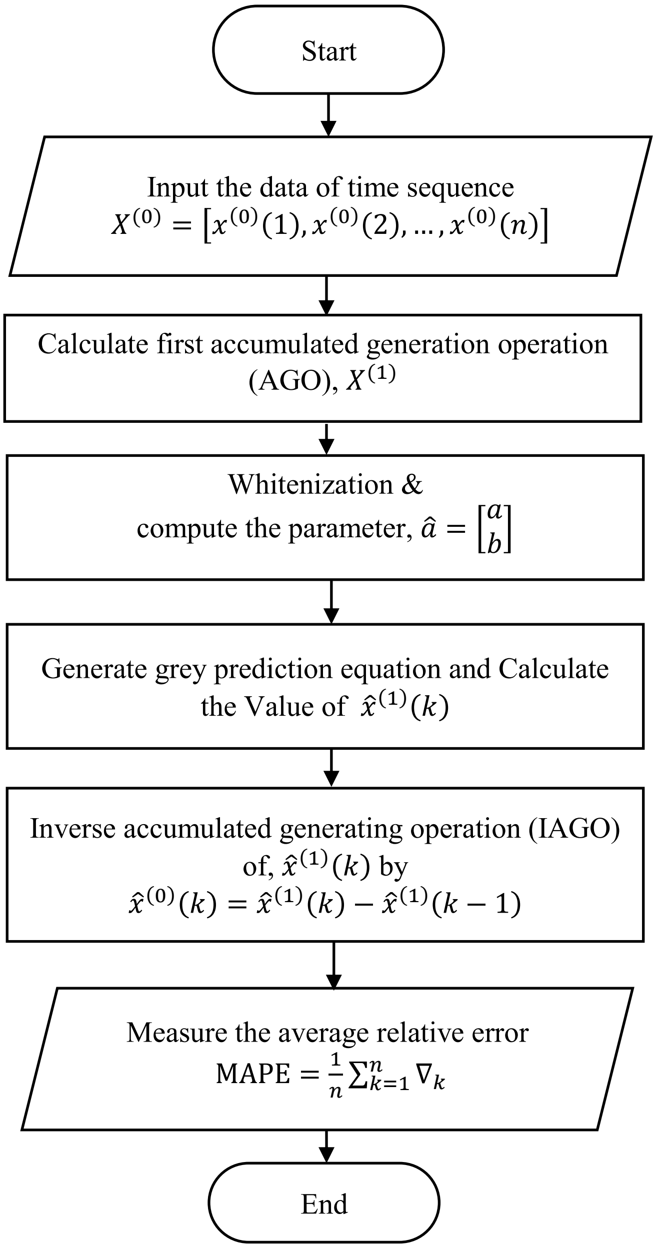


Figure 3.1: Flow chart of the basic GM (1,1) forecasting model.

3.2 Discrete Grey Model, DGM (1,1)

This study also considered the DGM (1, 1) model (Dong et al., 2017; Fei et al., 2011; B. Li et al., 2018; S. Liu et al., 2015; Yao et al., 2012), another basic form of the GM (1, 1) model to compare the forecasting accuracy of the GM (1, 1) model.

But there is a slight difference in parameter calculations from GM (1, 1) model. The following equation is used as the difference equation instead of the difference equation (3.4) in the DGM model as,

$$x^{(1)}(k+1) = \beta_1 x^{(1)}(k) + \beta_2 \tag{3.10}$$

Where, β_1 and β_2 are the coefficient of proportion parameters and the vector parameter $\hat{\beta} = [\beta_1, \beta_1]^{T}$ in equation (3.10) is analogous to the formula of the equation (3.6). There is also have a little difference in the formation of the matrix, B, and Y as,

$$B = \begin{bmatrix} -x^{(1)}(1) & 1 \\ -x^{(1)}(2) & 1 \\ \vdots & \vdots \\ -x^{(1)}(n-1) & 1 \end{bmatrix} \quad \text{and} \quad Y = \begin{bmatrix} x^{(1)}(2) \\ x^{(1)}(3) \\ \vdots \\ x^{(1)}(n) \end{bmatrix}.$$

Setting $x^{(1)}(1) = x^{(0)}(1)$, the time response formula for this model can be written as,

$$\hat{x}^{(1)}(k+1) = \beta_1^k \left(x^{(0)}(1) - \frac{\beta_2}{1-\beta_1} \right) + \frac{\beta_2}{1-\beta_1}, \quad k = 1,2,\dots,n-1. \tag{3.11}$$

The restored values of $\hat{x}^{(1)}(k)$ is $\hat{x}^{(0)}(k)$ that can be determined by the following equation,

$$\hat{x}^{(0)}(k+1) = \hat{x}^{(1)}(k+1) - \hat{x}^{(1)}(k), \qquad k = 1,2,\dots,n-1. \tag{3.12}$$

3.3 Particle Swarm Optimization (PSO)

The PSO method is becoming very popular due to its ease of implementation and the capacity to converge rapidly to the best solution. It requires only primitive mathematical operators and does not need the function's gradient information to optimize. Compared to other optimization methods, it is quicker and more powerful. (Bansal, 2019) explain clearly the working procedure of the PSO algorithm. According to the description, the PSO algorithm uses a parallel multi-agent scanning strategy, which carries on a swarm of particles, and each particle in the swarm provides a possible random solution. Each potential solution in the search space is termed as a particle, and the collection of the possible solutions is called a swarm. Within the search space, all particles move and change their location according to their own and neighboring experience. Learning from the particle's own experiences is called cognitive learning and learning from the other particles is called social learning. The particle stores its best memory from cognitive learning called p_{best} and the particle holds best memory from social learning referred as g_{best}.

A factor called velocity changes the direction and the magnitude of each particle regarding time, and time refers to the iteration in the PSO. For PSO, the velocity can be defined as the speed of change in the location concerning the iteration. For the N-dimensional search space, the optimization process of the PSO algorithm can be expressed as follows.

At time step t, the position of the i^{th} particle of the swarm in N-dimensional search space is defined by a vector of the same dimension, $x_i^t = (x_{i1}^t, x_{i2}^t, x_{i3}^t, \dots \dots, x_{iN}^t)^T$. The speed of that particle can also be expressed at the same time step t, by another vector of N-dimension, $v_i^t = (v_{i1}^t, v_{i2}^t, v_{i3}^t, \dots \dots, v_{iN}^t)^T$. The i^{th} particle's previously best-visited position at time step t is represented as $p_{best,i}^t = (p_{best1,i}^t, p_{best2,i}^t, p_{best3,i}^t, \dots \dots, p_{bestN,i}^t)^T$. The swarm's highest particle index is denoted by the global best, g_{best}. The i^{th} particle updates its velocity in the following way.

- **Update of the Velocity:**

$$v_{in}^{t+1} = v_{in}^t + c_1 r_1 \left[p_{best,in}^t - x_{in}^t\right] + c_2 r_2 \left[g_{best,n}^t - x_{in}^t\right] \tag{3.13}$$

Using the following position-update equation (3.14) to update the position.

- **Update of the Position:**

$$x_{in}^{t+1} = x_{in}^t + v_{in}^{t+1} \tag{3.14}$$

Considering the minimizing problem, the update formula for the optimal position of the individual particle is as follows,

- **Personal Best Update Equation:**

$$p_{best,in}^{t+1} = \begin{cases} p_{best,in}^t & if \quad f_{in}^{t+1} > p_{best,in}^t \\ x_{in}^{t+1} & if \quad f_{in}^{t+1} \le p_{best,in}^t \end{cases} \tag{3.15}$$

- **Global Best Equation:**

$$g_{best} = arg \max\ or\ min \{f(p^t_{best,i})\} \tag{3.16}$$

where $n = 1, 2, \ldots, N$ is the dimension and $i = 1, 2, \ldots, S$ indicates the particle index. The swarm size is denoted by the symbol S. The two constants c_1 and c_2 are acceleration coefficients—cognitive scaling and social scaling, respectively. Two random variables r_1 and r_2 are taking in the range of [0, 1] followed by a uniform distribution.

- **Stopping:**

Finally, a stopping criterion is needed to stop the algorithm, and it is not only a parameter for PSO but any meta-heuristic algorithm based on a population needs it. A usual geometric drawing of the motion of a particle in a second-dimensional space is shown in Figure 3.2, and the flow chart of the PSO algorithm is illustrated in Figure 3.3.

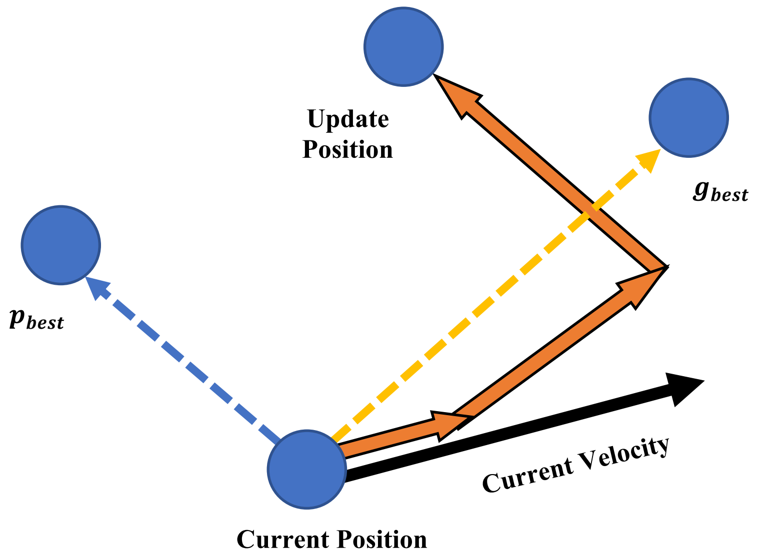


Figure 3.2: Geometric representation of the particle's motion in the PSO algorithm (Bansal, 2019).

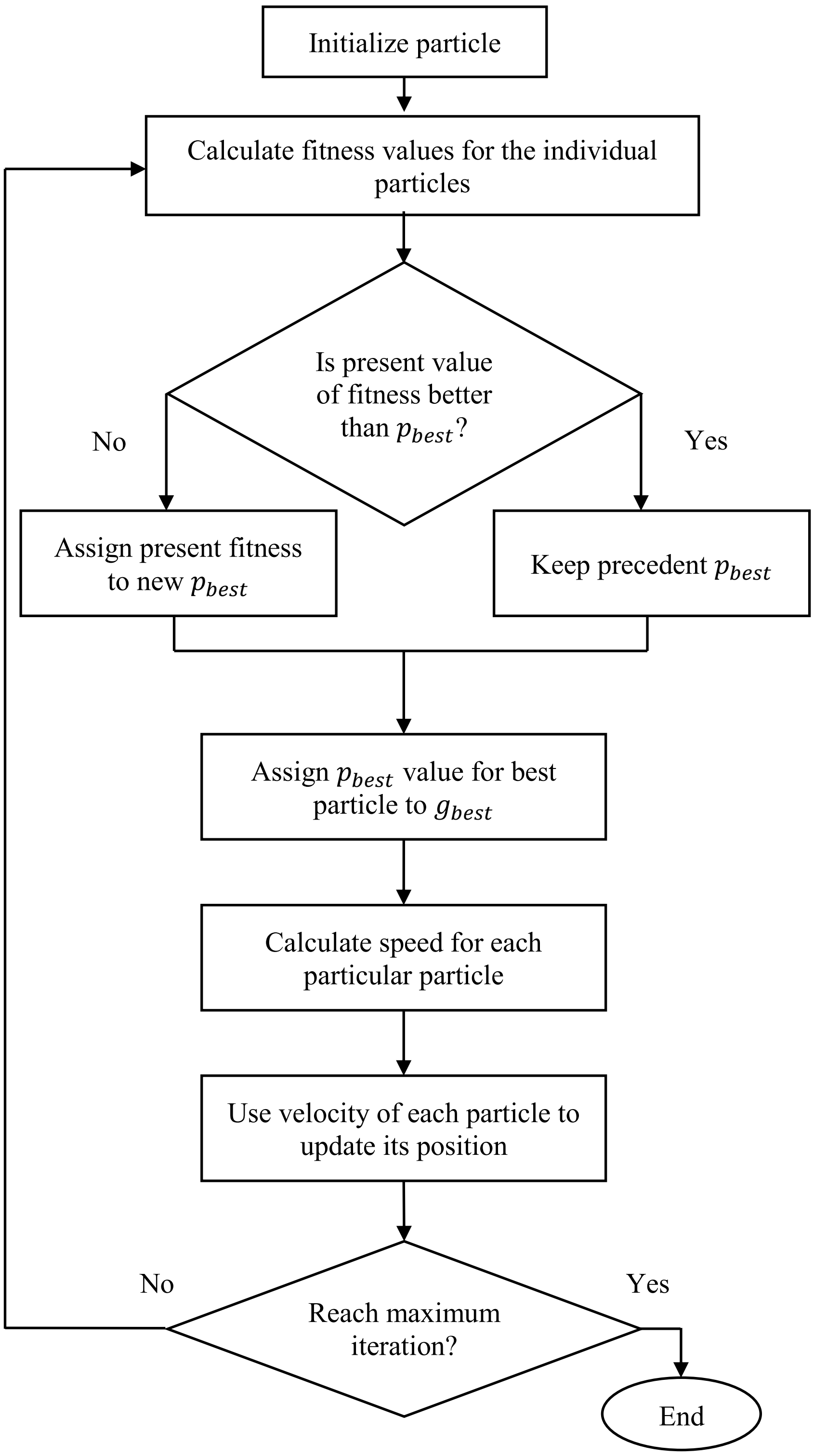


Figure 3.3: Flowchart of the basic PSO algorithm for the minimization problem.

- **Inertia Weight Strategy in PSO**

Inertia Weight performs a crucial role in the process of stabilizing the cycle of discovery and extraction. It determines the rate of contribution of the previous velocity of a particle to its speed in the current time step. Shi & Eberhart (2002) introduce an improved PSO algorithm shortly after the original PSO algorithm was proposed. The velocity update formula of the basic PSO was adopted with inertia weight, and the current velocity update formulation became:

$$v_{in}^{t+1} = \omega \times v_{in}^{t} + c_1 r_1 \left[p_{best,in}^{t} - x_{in}^{t}\right] + c_2 r_2 \left[g_{best,n}^{t} - x_{in}^{t}\right] \tag{3.17}$$

While this updated algorithm has nearly the same difficulty as the original version, the algorithm's efficiency has been significantly improved; thus, extensive applications have been achieved. There are several variants of the Inertia Weight Technique. Bansal et al. (2011) introduce fifteen relatively new and popular Inertia Weight strategies that are efficient than others.

3.4 Genetic Algorithm (GA)

The genetic algorithm (GA) is a computational technique for solving optimization problems. GA is a biologically inspired algorithm, which aims to replicate the basic Darwinian principles of natural selection “survival of the fittest.” This algorithm illustrates the natural selection process in which the most suitable individuals are chosen for reproduction to generate next-generation offspring. The following five phases constitute a classic genetic algorithm to generate the fittest candidates in every iteration (Kramer, 2017).

i. **Initial population**

   The cycle starts with a group of individuals called a Population. Every single individual is a possible solution to the optimization problem to solve. An individual has a set of modifications (variables) known as the Genes, which are combined to form a Chromosome string (solution). Each gene depicts a structurally distinct entity from the other genes.

ii. **Fitness function**

   The fitness function determines the fitness (an individual’s capacity to compete with the other individuals) of an individual to survive for the next iteration. It provides every single individual with a fitness score. The likelihood of selecting an individual for reproduction depends on its fitness value.

iii. **Selection**

The selection phase concept is to pick the most appropriate individuals and let them transfer their genes to the next iteration or generation. Two pairs of candidates (parents) are chosen based on their fitness values. High-fitness individuals have higher chances of being selected for reproduction.

iv. **Crossover**

In a genetic algorithm, the crossover is the most significant phase. It is an operator that enables the combination of two or more solutions with the ancestral chromosome. A crossover point from within the genes is selected at random for each pair of parents to be mated. From a biological viewpoint, two spouses of the same species merge their genetic material and transfer it to their offspring.

v. **Mutation**

Mutation operators by disturbing them alter a solution. The frequency of this upheaval is termed a rate of mutation. The mutation rate is also described as the step-size in continuous solution spaces. Any of its genes may be subjected to a mutation with a low random probability in some new offspring produced. Mutation operators have three main requirements: Accessibility, Unbiasedness, and Scalability (Kramer, 2017). Based on the above procedures of the GA pseudocode is summarized in Table 3.2.

Table 3.2: Pseudocode of Genetic Algorithm.

START
Initialize population (generate initial random chromosomes)
Set $\boldsymbol{i} = \mathbf{0}$; and $\boldsymbol{g}\ (\mathbf{0})$ as the generation of population;
REPEAT

- ***a.*** Compute fitness of each population
- ***b.*** Evaluate and ranked each population
- ***c.*** Select parent from $\boldsymbol{g}\ (\boldsymbol{i})$ based on the fitness of the population
- ***d.*** Apply crossover and mutation to parents and generate offspring
- ***e.*** Choose individuals from $\boldsymbol{g}\ (\boldsymbol{i})$ and offspring based on their fitness for the next generation $\boldsymbol{g}\ (\boldsymbol{i}+\mathbf{1})$
- ***f.*** Increment $\boldsymbol{i}$ as $\boldsymbol{i} = \boldsymbol{i} + \mathbf{1}$;

UNTIL the population has converged or maximum iteration
STOP

3.5 Analytic Hierarchy Process (AHP)

The following four described steps are used to implement the AHP method (Atanasova-pacemska et al., 2014):

a) It is creating a model of the hierarchical problem that we will agree on the model. The purpose (objective) holds the top of the hierarchy, parameters, sub-criteria, and alternatives are positioned at the bottom of the model. The following Figure 3.4 shows the structure.

b) Comparison is made in pairwise between the components of the structure at every level of the hierarchy. The priorities of the decision-makers are represented by the relative value levels of Saaty's scale. The scale includes five levels and four sub-levels defining the strength verbally, with corresponding numerical values ranging from 1 to 9, which is shown in the following table.

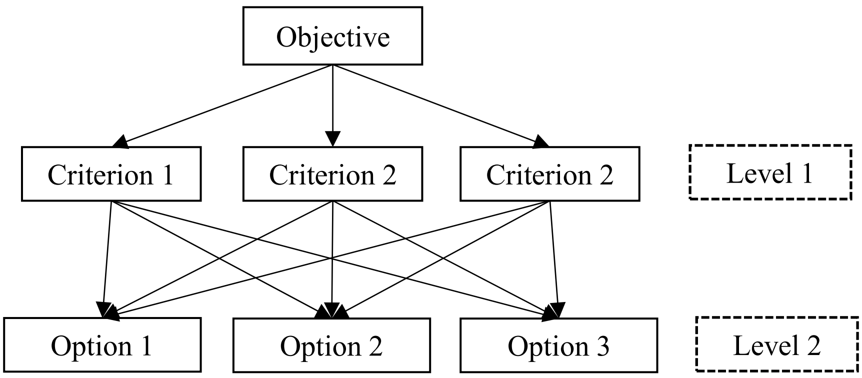


Figure 3.4: An illustration of the hierarchy of the AHP model.

Table 3.3: Saaty scale (Saaty, 1977).

Importance	Definition	Description
1	Equally important	Two elements contribution equal to the objective.
3	Moderately important	Moderately favor one element compared to the other.
5	Strong important	Strong favoring of one element compared to the other.
7	Very strong	One element is strongly favored and has domination in practice, compared to the other element.
9	Extreme importance	One element is strongly favored compared to the other
2, 4, 6, 8	Inter - values	Intermediate values between the two adjacent judgments
Reciprocals	If activity i has one of the above numbers, assigned compared as i to j, then j will have an inverse or reciprocal number in comparison to i.	

c) Evaluations of relative significance to the elements at each stage of the hierarchical system may be used to measure local requirements, sub-criteria, and alternatives. After that, the alternatives' overall preferences are synthesized. Every alternative's total importance is determined with the sum of local priorities that are weighted with weights of components from higher rates.
d) Finally, the sensitivity analysis is conducted.

3.5.1 Mathematical Model of AHP

If there is a comparison of n components, the results of the comparison build matrix C with dimension $n \times m$ where n is the number of criteria.

$$C = \begin{bmatrix} c_{11} & c_{12} & \cdots & c_{1m} \\ c_{21} & c_{22} & \cdots & c_{2m} \\ \vdots & \vdots & \vdots & \vdots \\ c_{n1} & c_{n2} & \cdots & c_{nm} \end{bmatrix} \tag{3.18}$$

The value of the i^{th} criterion relative to the j^{th} criterion is expressed by each entry c_{ij} of the matrix, C. If $c_{ij} > 1$, then the criterion i^{th} is more significant compared to the j^{th} criterion, and if $c_{ij} < 1$, then the comparison value will be reversed. The entry c_{ij} will be 1 when both the criteria have equal importance. The c_{ij} and c_{ji} entries obey the following requirement:

$$a_{ij} {*} a_{ji} = 1 \tag{3.19}$$

The comparative significance of the two criteria is calculated by a number scale displayed in Table 3.3. The next step is to obtain a normalized matrix $B = [b_{ij}]$ as follows:

$$b_{ij} = \frac{a_{ij}}{\sum_{i=1}^{n} a_{ij}} \tag{3.20}$$

The calculation of the weights, i.e. the eigenvector $W = [w_i]$ of the normalized matrix B, is carried out by computing the arithmetic mean according to the formula for each row of the matrix:

$$w_i = \frac{\sum_{j=1}^{n} b_{ij}}{n} \tag{3.21}$$

Finally, the consistency of the judgment is performed. Consistency means the decision-makers' clear opinion about the pairwise comparisons. Few contradictions can usually occur when several pairwise comparisons are conducted. Mathematically, the assessment matrix C is consistent if $a_{ik} = a_{ij} * a_{jk}$ for all i, j and k. According to Saaty (1977), consistency index, CI can be determined as:

$$\lambda_{max} = \sum_{i=1}^{n} \frac{(C.v)_i}{n.v_i} \tag{3.22}$$

Where n denotes the number of the matrix's independent rows, C represents the matrix of pair-wise comparison matrix, and v indicates the eigenvector of the matrix. Then the consistency index (CI) can be measured as:

$$CI = \frac{\lambda_{max} - n}{n - 1} \tag{3.23}$$

If $CI = 0$, then the matrix is entirely consistent. Indeed, the probability of consistency error is rising when dealing with raising the number of pair-wise comparisons. Thus Saaty (1980), proposed another CR (consistency ratio) metric that could be measured as,

$$CR = \frac{CI}{RI} \tag{3.24}$$

Where RI is the random consistency index of C, and its value is taken from Table 3.4 in which the first row (n) denotes the number of rows, i.e. matrix size, while the second row indicates random consistency. The CR value should be suggested less than 0.1 (Saaty, 1980).

Table 3.4: Table of random consistency index (Saaty, 1977).

n	3	4	5	6	7	8	9	10
RI	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.51

CHAPTER 4
RESEARCH METHODOLOGY

This chapter describes the successive procedures that were followed to conduct this research. The previous section clearly explains the theoretical framework of the basic grey prediction model, GM (1,1), as well as the underlying algorithms and methods followed by this study. For the betterment of the forecasted result of the GM (1,1) model, a PSO based integrated grey prediction method is proposed in this chapter which is used to predict the overall performance of the warehouse of an RMG industry of Bangladesh. Besides, the concept of major KPIs is also explained in detail in this chapter. Also, this chapter describes the parameter design of the optimization algorithms used in this study and the comparison of the performance of the proposed model with other grey models.

4.1 Research Methodology

This study aims to the betterment of the forecasted result of the GM (1, 1) model by proposing a new PSO based integrated grey prediction method called PSOGM (1, 1) and employing it into the prediction of the KPIs to estimate the overall performance of the warehouse of an RMG industry of Bangladesh. Besides, this research identifying the major KPIs of the warehouse to evaluate the overall performance and describes the parameter design of the optimization algorithms. The research methodology of this study is shown in the following Figure 4.1. The proposed methodology contains four major phases as,

a) Tuning parameters of the optimization algorithms used in this study.
b) Developing a PSO based integrated grey model, PSOGM (1, 1).
c) Identifying major KPIs for the RMG warehouse.
d) Evaluate the overall performance of the selected warehouse.

The details of these four phases can be covered by the following ten steps listed below.

(i) An integrated grey forecasting model based on the PSO algorithm, PSOGM (1, 1), is developed to optimize the traditional grey model's parameters a and b which are directly related to the accuracy of the forecasting of the GM (1, 1) model.

(ii) The objective function of the PSO algorithm is the minimization of errors associated with the simulated results outputted by the GM (1, 1) model. In this study, the Mean Absolute Error (MAPE) is chosen as the objective function for the PSO.

(iii) A pilot time series data is selected initially to compare the result obtained from the PSOGM (1, 1) with the Genetic Algorithm based grey model, GAGM (1, 1), and traditional grey model, GM (1, 1) and DGM (1, 1) based on the MAPE.

(iv) Before applying to the final prediction using the proposed model, the PSO and the GA algorithms are tuned by the Taguchi method for better search results using the MAPE as a test function for a known time series data.

(v) Then, various KPIs related to the warehouses, e.g., Storage Utilization, Units per Transaction, Order Picking/Packing Accuracy, Back Order Rate, Dock to Stock Time, Perfect Order Rate, Order Lead Time, Downtime in Proportion to Operating Time, Stock-out percentage, and On-Time Delivery percentage, etc. have been identified with exploring the literature review and the help of some experts in this field.

(vi) Next, three warehouses from three different companies in Bangladesh have been deliberately selected for collecting necessary data for the KPIs.

(vii) Now, the periodic indicators of the performance measurement are used as input for the selected grey models, and MAPE is measured for each KPI of each company to evaluate the efficiency of the proposed model for the practical data.

(viii) After selecting the best forecasting method, a case study is performed to predict the KPIs data of a warehouse of an RMG industry of Bangladesh up to the target period.

(ix) Then the forecasted KPIs value is used to measure the overall warehouse performance up to the target period through the weighted sum formula. Where the AHP method is employed to determine the weights of the KPIs.

(x) The simulation and statistical analyses are carried out for both the traditional and proposed models in MATLAB software. The excel tool is also used for the AHP method applied to prioritize the selected KPIs parallel to the strategy of the organizations.

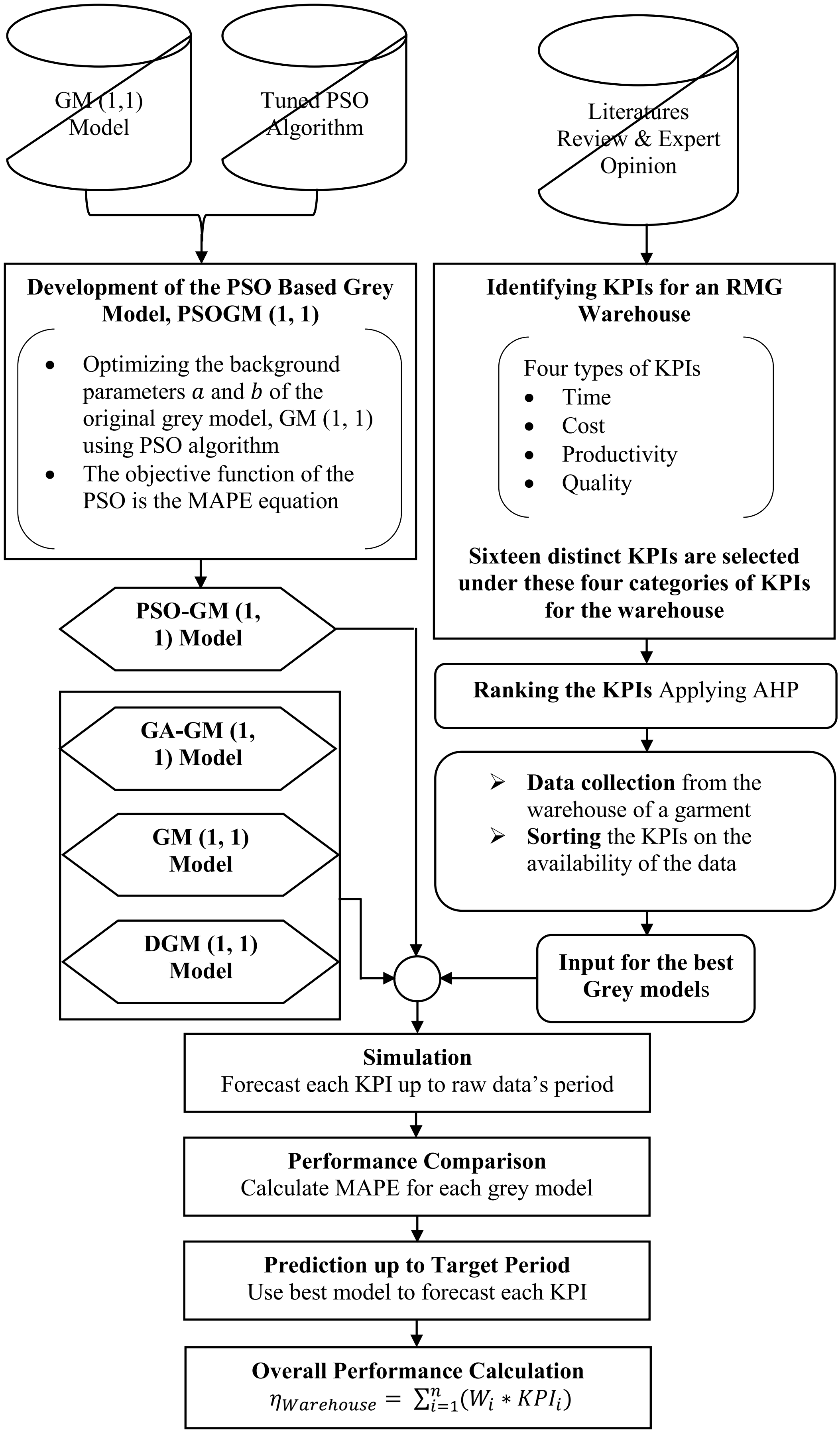


Figure 4.1: Proposed framework of the research.

4.2 Development of Integrated PSO Based-Grey Model

Input for the model:

Three inputs are required for the model: (a) The raw data series, $X^{(0)}$ having the sample size of n data points for the GM (1, 1) model as

$$X^{(0)} = \left[x^{(0)}(1), x^{(0)}(2), \dots, x^{(0)}(n)\right], \qquad n \geq 4 \tag{4.1}$$

(b) Input for the parameters, and objective function, here the MAPE function is used, of PSO algorithm, and (c) Logical ranges of the development coefficient, $\boldsymbol{a}$ and the control coefficient, $\boldsymbol{b}$ for the proposed model are set from the equation of mean sequence generation of the GM (1, 1) model for the three values of positioned coefficient, α as $\alpha = 0.0;$ $\alpha = 0.5;$ and $\alpha = 1.0$. The equations are as follows,

$$Z^{(1)}(k) = x^{(1)}(k-1), \qquad k = 2,3, \dots \dots, n. \tag{4.2a}$$

$$Z^{(1)}(k) = 0.5 * x^{(1)}(k) + 0.5 * x^{(1)}(k-1), \qquad k = 2,3, \dots \dots, n. \tag{4.2b}$$

$$Z^{(1)}(k) = x^{(1)}(k), \qquad k = 2,3, \dots \dots, n. \tag{4.2c}$$

Then, the following equation is used to measure the values of a and b for each equation.

$$\hat{a} = \begin{bmatrix} a \\ b \end{bmatrix} = [B^T B]^{-1} B^T\, Y \tag{4.3}$$

From the calculated values for the coefficients, a, and b, the maximum and minimum values are selected to set the boundary of those parameters.

Building the model:

Step 1. Consider, a swarm of particles with locations $[x_i = x_{i1}, x_{i2}, \dots, x_{iN}]$ and velocities $[v_i = v_{i1}, v_{i2}, \dots, v_{iN}]$, are initialized randomly in the solution space. Where, $i =$

$1, 2, \ldots, S$, indicates the particle index, $n = 1, 2, \ldots, N$, is the dimension of the search space, and the symbol S denotes the swarm size.

Step 2. Evaluation of all particles' fitness values as,

$$f(\mathrm{x}) = \mathrm{MAPE} = \frac{1}{n}\sum_{k=1}^{n} \frac{\left|x^{(0)}(k) - \hat{x}^{(0)}(k)\right|}{x^{(0)}(k)} \quad k = 1,2, \ldots \ldots, n \tag{4.4}$$

Where, n indicates the sample size, $x^{(0)}(k)$ indicates raw data, and $\hat{x}^{(0)}(k)$ indicates the predicted value of the raw data. The predicted value, $\hat{x}^{(0)}(k)$ is determined from the following equations,

$$\hat{x}^{(1)}(k) = \left[x^{(0)}(1) - \frac{b}{a}\right] e^{-a(k-1)} + \frac{b}{a} \tag{4.5}$$

$$\hat{x}^{(0)}(k) = \hat{x}^{(1)}(k) - \hat{x}^{(1)}(k-1), \;\; k = 2,3, \ldots, n \tag{4.6}$$

Step 3. The speed and location of each particle in search space is constantly updated according to the following equations:

$$v_{in}^{t+1} = W \times v_{in}^{t} + c_1 r_1^t \left[p_{best,in}^{t} - x_{in}^{t}\right] + c_2 r_2^t \left[g_{best,n}^{t} - x_{in}^{t}\right] \tag{4.7}$$

$$x_{in}^{t+1} = x_{in}^{t} + v_{in}^{t+1} \tag{4.8}$$

In the above equation, the cognitive coefficient c_1 and social acceleration coefficient c_2 are two constants in [0, 2], and the random variables r_1^t and r_2^t are taken in each iteration randomly in the range of [0, 1]. W indicates the inertia weight, which value can be updated at every iteration according to some formula and follows a range of [0, 1].

Step 4. Determining each particle's Personal Best, $p_{best,in}^{t}$ for minimizing problem as,

$$p_{best,in}^{t+1} = \begin{cases} p_{best,in}^{t} & if \quad f_{in}^{t+1} > p_{best,in}^{t} \\ x_{in}^{t+1} & if \quad f_{in}^{t+1} \leq p_{best,in}^{t} \end{cases} \tag{4.9}$$

Step 5. Evaluation of the Global Best, $g_{best,n}^{t}$ as,

$$g_{best,n}^{t} = arg\max\ or\ min\left\{f\left(p_{best,i}^{t}\right)\right\} \tag{4.10}$$

Step 6. Updating the iteration number by $t = t + 1$. Then go to '**Step 2**' and repeat the cycle until the iteration number exceeds the t_{max}. After completing this process, a particle with the best functional value is found, and the corresponding location of that particle indicates an optimal result for coefficients a and b of the GM (1, 1) model.

Step 7. The optimized values, a^{opt} and b^{opt} of the gray coefficients, a and b respectively obtained from the above steps, are used in the grey time series forecasting equation as follows,

$$\hat{x}^{(1)}(k) = \left[x^{(0)}(1) - \frac{b^{opt}}{a^{opt}}\right]e^{-a^{opt}(k-1)} + \frac{b^{opt}}{a^{opt}} \tag{4.11}$$

After then, the forecasting value of the original raw data is performed by the IAGO operation by the following formula:

$$\hat{x}^{(0)}(k) = \hat{x}^{(1)}(k) - \hat{x}^{(1)}(k-1),\ \ k = 2,3,\dots,n \tag{4.12}$$

In the following Table 4.1 displays the pseudocode of the proposed predictive model, PSOGM (1, 1).

Table 4.1: Pseudocode of PSOGM (1, 1) model.

START
Input the historical data series
Set PSO Parameters
Set the boundary for the grey coefficients $\boldsymbol{a}$ and $\boldsymbol{b}$
Initialize population
REPEAT

- ***a.*** Evaluate the attribute fitness
- ***b.*** Determine the best value and correlate it to the one recently discovered for each attribute
- ***c.*** The location of the best fitness function is Personal Best, $\boldsymbol{p_{best}}$
- ***d.*** Keep comparing Fitness Analysis to the overall $\boldsymbol{p_{best}}$
- ***e.*** Among all the $\boldsymbol{p_{best}}$ the best value is the Global Best, $\boldsymbol{g_{best}}$
- ***f.*** Velocity and location upgraded and generate a new population
- ***g.*** Increment $\boldsymbol{t}$ as $\boldsymbol{t = t + 1}$

UNTIL the population has converged or maximum iteration, $\boldsymbol{t_{max}}$

h. The optimized values, $\boldsymbol{a^{opt}}$ and $\boldsymbol{b^{opt}}$ of the gray coefficients are obtained

i. Grey time series forecasting equation is applied

j. Forecasting of the original raw data is performed by the IAGO operation

STOP

4.3 Parameter Settings of Optimization Algorithms

The objective of parameter optimization is to determine the parameter values for an algorithm that leads to optimal results, which indicates the quality and robustness of the solution. This study employs the Taguchi experimental design, developed by Genichi Taguchi (Freddi & Salmon, 2019) for the tuning of the parameters of the PSO and GA optimization algorithms prior to their combination with the GM (1, 1) model. This works on the orthogonal array for parameter design. According to this method, Taguchi suggests that the critical index of the signal-to-noise (S/N) ratio determines the degree of variability in the response variable. A higher S/N value is recommended. In the Taguchi process, the S/N ratio is determined for the minimizing objectives through the following equation:

$$S/N = -10 \times log_{10}^{(MAPE)^2} \tag{4.13}$$

Where the equation of MAPE is used as the objective function for PSO and GA. Table 4.3 shows the list of parameters alongside their levels for each algorithm. A maximum of four levels is considered for each parameter to design the experiments.

Table 4.2: The optimization algorithm's parameters and their levels.

Algorithm	Factors	Levels			
		1	2	3	4
PSO	Maximum Iteration (Maxit)	50	100	300	700
	Population Size (Npop)	10	30	50	100
	Acceleration Coefficient (C1)	0.5	1.0	1.5	2.0
	Acceleration Coefficient (C2)	0.5	1.0	1.5	2.0
	Strategy of Inertia Weight (W)	1	2	3	4
GA	Number of Population (Npop)	10	30	50	100
	Crossover Probability (CP)	0.4	0.6	0.8	0.9
	Uniform Mutation Rate (MR)	0.01	0.03	0.05	0.1
	Number of Generations (Gen)	50	100	200	500

For the inertia weight calculation in the PSO, four distinct popularly used strategies are selected from fifteen possible strategies (Bansal et al., 2011). The numeric number, 1-4 in the table for the factor, Strategy of Inertia Weight (W), indicates the following inertia strategy consequently.

Strategy-1: Constant value is set for W, as W = 0.7.

Strategy-2: Linearly decreased inertia weight is generated by:

$$W = W_{max} - ((W_{max} - W_{min})/t_{max}) \times t$$

Strategy-3: Random Inertia Weight

$$W = 0.5 + \frac{Rand\ ()}{2}$$

Strategy-4: Here, W is generated as,

$$W = W_{min} + \left(\frac{W_{max} - W_{min}}{t_{max}}\right) \times \lambda^{(t-1)}$$

In the above strategies, W_{max} and W_{min} express the highest and lowest values of the inertia weight which generally set as $W_{max} = 0.90$ and $W_{min} = 0.10$ and t_{max} denotes the maximum number of iterations. The value of the λ is set as 0.95, and t indicates the iteration number.

Primarily, this process considers a six-sample data series, $X^{(0)} = (60.7, 73.8, 86.2, 100.4, 123.3, 149.5)$ from (Liu et al., 2016, p. 166). The average response value of MAPE obtained from the PSOGM (1, 1) and GAGM (1, 1), is used to the Taguchi analysis. The Percent of Relative Deviation (PRD) method is used to calculate the efficiency of algorithms. PRD on the minimizing problems can be considered as the formula below:

$$PRD = \frac{Alg_{Response} - Min_{Response}}{Max_{Response} - Min_{Response}} \tag{4.14}$$

Where $Min_{Response}$ and $Max_{Response}$ represent the best and worse response among all solutions and $Alg_{Response}$ is the solution of the algorithm. According to the number of levels and parameters in Table 4.2, the Taguchi process for PSO and GA has proposed L16. Table 4.3 and Table 4.4 show the orthogonal arrays of L16 for PSO and GA to do the Taguchi experiments. Additionally, for each algorithm, the S/N ratio and mean PRD are shown in Figure 4.2–4.5.

Table 4.3: The orthogonal array, L16 for the PSO.

Run	Maxit	Npop	C1	C2	W
1	50	10	0.5	0.5	1
2	50	30	1.0	1.0	2
3	50	50	1.5	1.5	3
4	50	100	2.0	2.0	4
5	100	10	1.0	1.5	4
6	100	30	0.5	2.0	3
7	100	50	2.0	0.5	2
8	100	100	1.5	1.0	1
9	300	10	1.5	2.0	2
10	300	30	2.0	1.5	1
11	300	50	0.5	1.0	4
12	300	100	1.0	0.5	3
13	700	10	2.0	1.0	3
14	700	30	1.5	0.5	4
15	700	50	1.0	2.0	1
16	700	100	0.5	1.5	2

Table 4.4: The orthogonal array, L16 for the GA.

Run	Npop	CP	MR	Gen
1	10	0.4	0.01	50
2	10	0.6	0.03	100
3	10	0.8	0.05	200
4	10	0.9	0.1	500
5	30	0.4	0.03	200
6	30	0.6	0.01	500
7	30	0.8	0.1	50
8	30	0.9	0.05	100
9	50	0.4	0.05	500
10	50	0.6	0.1	200
11	50	0.8	0.01	100
12	50	0.9	0.03	50
13	100	0.4	0.1	100
14	100	0.6	0.05	50
15	100	0.8	0.03	500
16	100	0.9	0.01	200

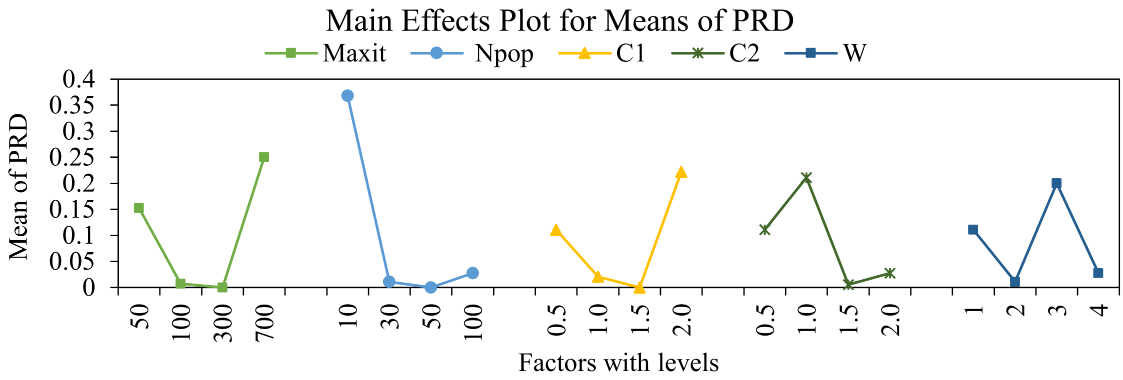


Figure 4.2: Main Effects Plot for Means of PRD for PSO's parameters.

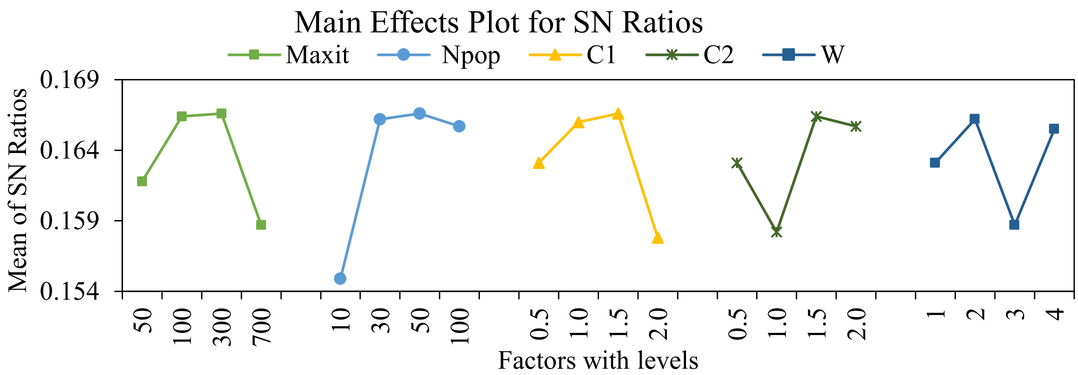


Figure 4.3: Main Effects Plot for S/N Ratios for PSO's parameters.

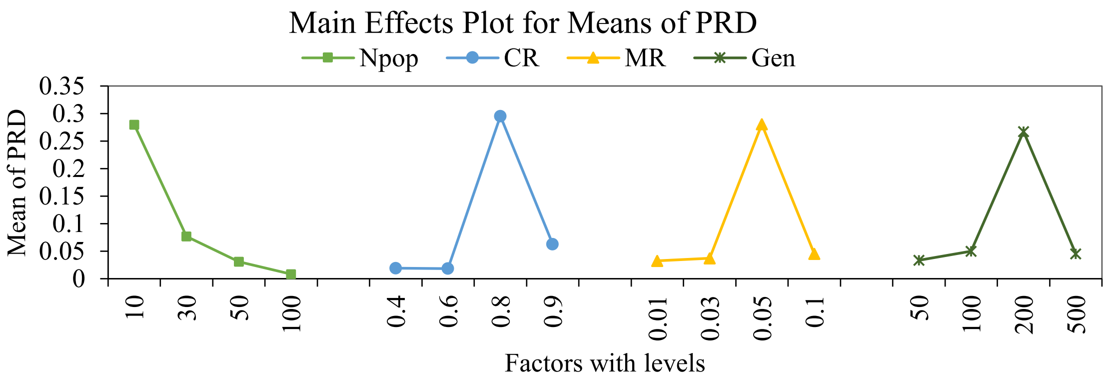


Figure 4.4: Main Effects Plot for Means of PRD for GA's parameters.

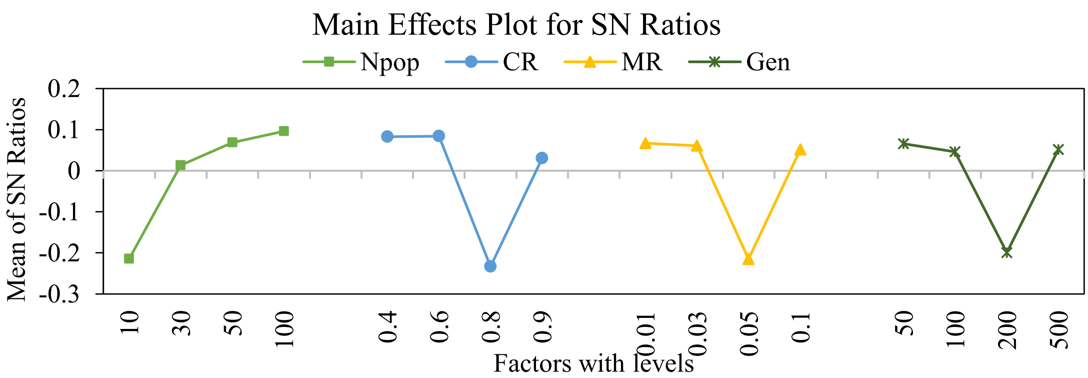


Figure 4.5: Main Effects Plot for S/N Ratios for GA's parameters.

Analyzing these figures and depending on the Taguchi analysis, the best level for each selected parameter in PSO and GA displayed in Table 4.5. The higher the S/N value the lower RPD value are for a minimization optimization model, the better the algorithm's efficiency.

Table 4.5: The best parameters level for each algorithm.

Algorithm	Factors	Best level
PSO	Maximum Iteration (Maxit)	300
	Population Size (Npop)	50
	Acceleration Coefficient (C1)	1.5
	Acceleration Coefficient (C2)	1.5
	Strategy of Inertia Weight (W)	2
GA	Number of Population (Npop)	100
	Crossover Probability (CP)	0.6
	Uniform Mutation Rate (MR)	0.01
	Number of Generations (Gen)	50

4.4 Comparing the Performance of Proposed Model

In this section, the performance of the tuned PSO based grey model, PSOGM (1, 1), is compared with other grey models. For this comparison, this study considered two basic grey model called GM (1, 1) and DGM (1, 1) along with a hybrid grey model based on the tuned genetic algorithm called GAGM (1, 1). Continue this step, a new time series data of thirteen samples is chosen from the same source of the previous data (Liu et al., 2016, p. 163). This time a randomly variated data series is taken for this analysis. The pilot data series is as follows,

$$X^{(0)} = (6, 20, 40, 25, 40, 45, 35, 21, 14, 18, 15.5, 17, 15)$$

The simulation result obtained from the four grey models at their optimum parameter setting is presented in the following Table 4.6. The table shows that the MAPE of PSOGM (1, 1) is lower than other models. The corresponding Figure 4.6 shows the actual data with simulated data. According to Figure 4.6, the simulated curve of the PSOGM (1, 1) is very closely fitted with the final trend of the original data series than other grey models' simulated curves. Figure 4.7 shows the interval plot of the absolute percent error at 95 % confidence interval (CI) which illustrates the statistical significance of the simulation of the four grey models. It is evident in the figure that the mean MAPE of the PSOGM (1, 1) is lower as well as the margin of error or the level of the CI.

Table 4.6: Simulation of selected data series.

Actual Data	Simulated Data				Absolute Percent Error (%)			
	PSOGM (1, 1)	GAGM (1, 1)	DGM (1, 1)	GM (1, 1)	PSOGM (1, 1)	GAGM (1, 1)	DGM (1, 1)	GM (1, 1)
6	6.00	6.00	6.00	6.00	0.00	0.00	0.00	0.00
20	28.01	35.16	36.35	35.67	40.03	75.78	81.73	78.35
40	26.46	32.88	33.91	33.43	33.85	17.80	15.21	16.42
25	25.00	30.75	31.65	31.33	0.00	23.02	26.58	25.32
40	23.62	28.76	29.53	29.36	40.95	28.09	26.18	26.59
45	22.32	26.90	27.55	27.52	50.41	40.22	38.77	38.85
35	21.09	25.16	25.71	25.79	39.75	28.11	26.54	26.31
21	19.92	23.53	23.99	24.17	5.13	12.06	14.24	15.10
14	18.82	22.01	22.39	22.65	34.45	57.22	59.89	61.81
18	17.78	20.59	20.89	21.23	1.20	14.37	16.04	17.95
15.5	16.80	19.25	19.49	19.90	8.41	24.22	25.74	28.37
17	15.88	18.01	18.19	18.65	6.61	5.93	6.98	9.69
15	15.00	16.84	16.97	17.48	0.00	12.28	13.13	16.51
				MAPE (%)	**20.06**	**26.08**	**27.00**	**27.79**

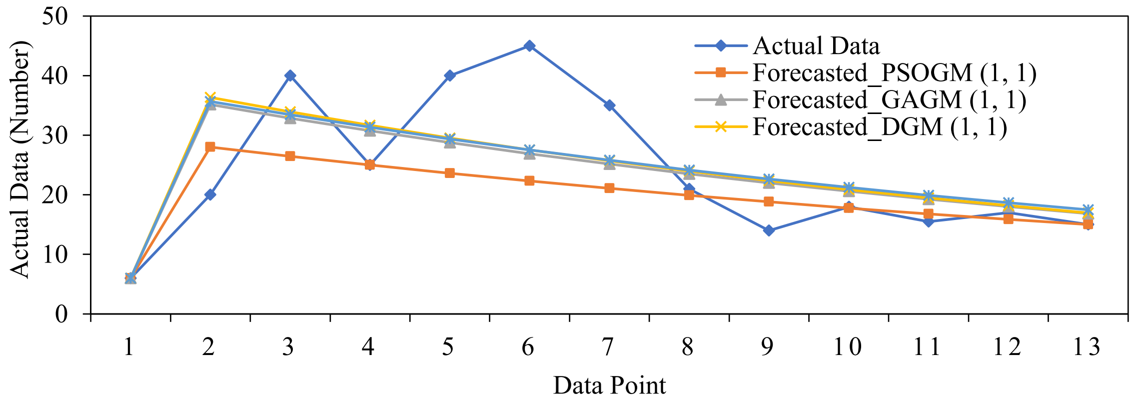


Figure 4.6: Illustration of the actual and simulated data of the selected series.

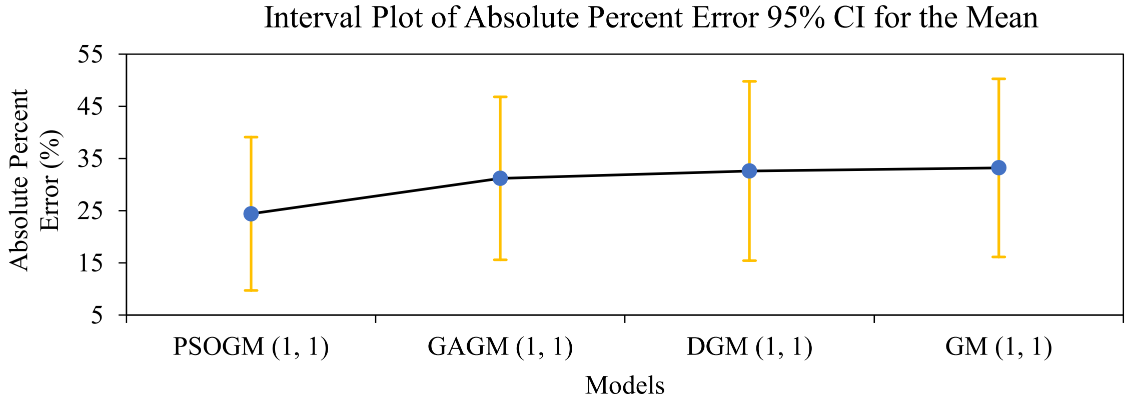


Figure 4.7: Interval Plot of errors for the four grey models.

In all aspects of the above analysis, the proposed model over the other three models.

4.5 Conceptualization of the KPIs

A KPI is a quantitative measurement that shows how successfully a firm achieves core business goals. It supports institutions to determine their achievement of goals. The managers use two forms of KPIs. One is low-level KPIs that can rely on processes or personnel in divisions such as promotions, accounting, or service centers. At the same time, high-level KPIs often reflect on the company's overall efficiency.

Warehousing has become a critical element in both the supply chain and manufacturing. Properly managing the warehouse is a challenging job for the manger. KPIs are act as a core tools for warehouse performance assessment. KPIs are process-specific characteristics that are calculated to define whether the process is carried out compared to preset standards. To determine the overall efficiency of an RMG warehouse, important KPIs need to be established. A summary of the selected KPIs of this study is displayed in (Appendix E).

CHAPTER 5
IMPLEMENTATION OF PROPOSED MODEL

This chapter represents the numerical implementation of the proposed grey model in real-life data series. Here a case study is presented to predict the future performance of a warehouse of an RMG industry of Bangladesh trough the proposed model to take the control actions beforehand by the manager accordingly. Before predicting the overall performance, this chapter describes the data collection of the selected KPIs of that warehouse and the ranking of the KPIs through the AHP process. Finally, the individual KPI is forecasted up to a target period using the best grey model. Then the overall performance of the warehouse is measured by the weighted sum method. This chapter also explains the simulation of KPIs data for two other warehouses of two different companies to support the proposed model's performance over the other grey methods.

5.1 Data Collection

The KPIs data for three warehouses is collected from the three different companies which are the Best Shirts Ltd., Gazipur, Bangladesh, the Ever-Smart Bangladesh Ltd., Gazipur, Bangladesh, and Brothers Furniture Ltd., Saver, Bangladesh. Among these three warehouses, the data of Best Shirts Ltd. is used to measure the overall warehouse performance up to a target period and the other two warehouses data are used only for simulation purposes to see the performance of the proposed model over the selected other grey models.

The selected companies are renowned industries of Bangladesh and its warehouses partially perform all the essential warehouse functions. A senior executive of IE (Industrial Engineering), a planning officer, and three other officers provide the information of the KPIs of each company. The following Table 5.1 represents the historical KPIs data of Best Shirts Ltd. and a detailed description of this data along with the other two warehouses' KPIs data are displayed in (Table C1 - Table C6 of Appendix-C). Since different industries maintain various KPIs of the warehouse, the availability of the KPIs data was not the same for all three warehouses. Regarding the matter, a maximum of 13 KPIs data has been managed among the primarily selected 16 KPIs of the warehouses of the three industries.

Table 5.1: The actual KPIs data of the Best Shirt Ltd. warehouse.

SL	KPIs	Months						Standard
		Sep-19	Oct-19	Nov-19	Dec-19	Jan-20	Feb-20	
1	Inventory Turnover	1.21	1.29	1.33	1.08	1.30	1.24	1.20
2	Inventory to Sales Ratio	0.82	0.79	0.77	0.92	0.64	0.80	0.80
3	Store Utilization	95.86	85.64	77.56	85.19	85.26	88.27	90.00
4	Orders per hour	223.45	172.50	198.62	206.90	189.09	188.50	185.00
5	Inventory Accuracy (0 to 1 scale)	0.91	1.00	1.00	0.92	1.00	0.98	1.00
6	Stock-out Percentage	2.27	2.65	2.47	3.53	2.60	2.80	1.75
7	Perfect Order Rate	0.91	0.95	0.83	0.97	0.90	0.96	0.98
8	Order Lead Time (Days)	88	92	90	85	100	88	87
9	Downtime to Operating Time Ratio	0.022	0.037	0.032	0.035	0.025	0.028	0.100
10	On-time Delivery (%)	96	99	97	100	95	98	100
11	Cost per Order ($)	173.71	317.43	145.25	183.00	168.00	195.00	250.00
12	Carrying Cost of Inventory ($)	6150	6500	6000	6400	5600	6720	6000
13	Labor Cost ($)	10100	9375	10688	9125	9750	10875	10000

According to Table 5.1, the data of the thirteen KPIs among primarily selected sixteen KPIs are collected for six months, September 2019 to February 2020, with their standard values that are desired by the manager as well as the company. In the Table, the standard values indicate the target point set by the authority. The most recent data is unavailable due to the COVID-19 pandemic as the production has been disrupted.

5.2 Simulation and Prediction of KPIs

The simulation and the prediction of each KPI are performed using the MATLAB software version R2017a. A MATLAB code of the proposed grey model, PSOGM (1, 1) is included in (Appendix-B). The following Table 5.2 shows the simulation with error associated with the simulation for the selected KPIs of the warehouse of the Best Shirt Ltd and Table 5.3 represents the overall summary of error of this simulation for the three selected warehouses. Analyzing the results of the table, the best model is used to construct Table 5.4. The graphical illustration of the results obtained from four grey models is depicted in Figure 5.1 for the Best Shirt Ltd. and Figure 5.2 illustrates the overall error generated for each KPI for each grey model for the three selected warehouses.

Table 5.2: Simulation of each KPI for the warehouse of Best Shirt Ltd. [A-M].

A. KPI-1: Inventory Turnover

Period	Actual	Forecasted				Absolute Relative Error			
		GM (1, 1)	**DGM (1, 1)**	**GAGM (1, 1)**	**PSOGM (1, 1)**	**GM (1, 1)**	**DGM (1, 1)**	**GAGM (1, 1)**	**PSOGM (1, 1)**
Sep-19	1.210	1.210	1.210	1.210	1.210	0.00%	0.00%	0.00%	0.00%
Oct-19	1.290	1.275	1.278	1.278	1.290	1.19%	0.95%	0.96%	0.00%
Nov-19	1.330	1.261	1.263	1.266	1.277	5.17%	5.06%	4.84%	3.96%
Dec-19	1.080	1.248	1.248	1.254	1.265	15.54%	15.54%	16.09%	17.11%
Jan-20	1.300	1.235	1.233	1.242	1.252	5.03%	5.15%	4.45%	3.67%
Feb-20	1.240	1.222	1.218	1.230	1.240	1.49%	1.73%	0.77%	0.00%
					MAPE	4.74%	4.74%	4.52%	**4.12%**

B. KPI-2: Inventory to Sales Ratio

Period	Actual	Forecasted				Absolute Relative Error			
		GM (1, 1)	**DGM (1, 1)**	**GAGM (1, 1)**	**PSOGM (1, 1)**	**GM (1, 1)**	**DGM (1, 1)**	**GAGM (1, 1)**	**PSOGM (1, 1)**
Sep-19	0.820	0.820	0.820	0.820	0.820	0.00%	0.00%	0.00%	0.00%
Oct-19	0.790	0.806	0.811	0.798	0.790	2.02%	2.63%	1.04%	0.00%
Nov-19	0.770	0.795	0.797	0.785	0.792	3.22%	3.52%	1.94%	2.92%
Dec-19	0.920	0.784	0.784	0.772	0.795	14.80%	14.82%	16.10%	13.59%
Jan-20	0.640	0.773	0.771	0.759	0.797	20.78%	20.39%	18.60%	24.61%
Feb-20	0.800	0.762	0.758	0.746	0.800	4.71%	5.31%	6.70%	0.00%
					MAPE	7.59%	7.78%	7.40%	**6.85%**

C. KPI-3: Store Utilization

Period	Actual	Forecasted				Absolute Relative Error			
		GM (1, 1)	**DGM (1, 1)**	**GAGM (1, 1)**	**PSOGM (1, 1)**	**GM (1, 1)**	**DGM (1, 1)**	**GAGM (1, 1)**	**PSOGM (1, 1)**
Sep-19	95.86	95.86	95.86	95.86	95.86	0.00%	0.00%	0.00%	0.00%
Oct-19	85.64	81.77	81.82	82.50	82.22	4.52%	4.45%	3.66%	4.00%
Nov-19	77.56	83.05	83.09	83.82	83.69	7.08%	7.12%	8.07%	7.90%
Dec-19	85.19	84.36	84.36	85.15	85.19	0.97%	0.97%	0.04%	0.00%
Jan-20	85.26	85.69	85.66	86.51	86.72	0.50%	0.47%	1.46%	1.71%
Feb-20	88.27	87.04	86.98	87.89	88.27	1.39%	1.46%	0.44%	0.00%
					MAPE	2.41%	2.41%	2.28%	**2.27%**

D. KPI-4: Orders Per Hour

Period	Actual	Forecasted				Absolute Relative Error			
		GM (1, 1)	**DGM (1, 1)**	**GAGM (1, 1)**	**PSOGM (1, 1)**	**GM (1, 1)**	**DGM (1, 1)**	**GAGM (1, 1)**	**PSOGM (1, 1)**
Sep-19	223.45	223.45	223.45	223.45	223.45	0.00%	0.00%	0.00%	0.00%
Oct-19	172.50	186.83	187.15	184.93	190.87	8.31%	8.49%	7.20%	10.65%
Nov-19	198.62	188.95	189.12	186.88	190.28	4.87%	4.78%	5.91%	4.20%
Dec-19	206.90	191.10	191.11	188.85	189.68	7.64%	7.63%	8.72%	8.32%
Jan-20	189.09	193.27	193.12	190.85	189.09	2.21%	2.13%	0.93%	0.00%
Feb-20	188.50	195.46	195.15	192.86	188.50	3.69%	3.53%	2.32%	0.00%
					MAPE	4.45%	4.43%	4.18%	**3.86%**

E. KPI-5: Inventory Accuracy

Period	Actual	Forecasted				Absolute Relative Error			
		GM (1, 1)	**DGM (1, 1)**	**GAGM (1, 1)**	**PSOGM (1, 1)**	**GM (1, 1)**	**DGM (1, 1)**	**GAGM (1, 1)**	**PSOGM (1, 1)**
Sep-19	0.910	0.910	0.910	0.910	0.910	0.00%	0.00%	0.00%	0.00%
Oct-19	1.000	0.988	0.989	0.990	1.000	1.19%	1.14%	1.05%	0.00%
Nov-19	1.000	0.984	0.984	0.986	0.995	1.60%	1.57%	1.43%	0.50%
Dec-19	0.920	0.980	0.980	0.982	0.990	6.52%	6.52%	6.72%	7.60%
Jan-20	1.000	0.976	0.976	0.978	0.985	2.41%	2.43%	2.20%	1.50%
Feb-20	0.980	0.972	0.971	0.974	0.980	0.82%	0.87%	0.59%	0.00%
					MAPE	2.09%	2.09%	2.00%	**1.60%**

F. KPI-6: Stock-out Percentage

Period	Actual	Forecasted				Absolute Relative Error			
		GM (1, 1)	**DGM (1, 1)**	**GAGM (1, 1)**	**PSOGM (1, 1)**	**GM (1, 1)**	**DGM (1, 1)**	**GAGM (1, 1)**	**PSOGM (1, 1)**
Sep-19	2.27	2.27	2.27	2.27	2.27	0.00%	0.00%	0.00%	0.00%
Oct-19	2.65	2.73	2.75	2.65	2.65	2.96%	3.84%	0.05%	0.00%
Nov-19	2.47	2.77	2.78	2.68	2.69	12.09%	12.58%	8.49%	8.77%
Dec-19	3.53	2.81	2.81	2.71	2.72	20.41%	20.40%	23.28%	22.83%
Jan-20	2.60	2.85	2.84	2.74	2.76	9.65%	9.21%	5.27%	6.22%
Feb-20	2.80	2.89	2.87	2.77	2.80	3.32%	2.48%	1.21%	0.00%
					MAPE	8.07%	8.09%	6.38%	**6.30%**

G. KPI-7: Perfect Order Rate

Period	Actual	Forecasted				Absolute Relative Error			
		GM (1, 1)	DGM (1, 1)	GAGM (1, 1)	PSOGM (1, 1)	GM (1, 1)	DGM (1, 1)	GAGM (1, 1)	PSOGM (1, 1)
Sep-19	0.910	0.910	0.910	0.910	0.910	0.00%	0.00%	0.00%	0.00%
Oct-19	0.950	0.904	0.905	0.911	0.950	4.86%	4.72%	4.11%	0.00%
Nov-19	0.830	0.913	0.914	0.921	0.952	9.98%	10.06%	10.93%	14.76%
Dec-19	0.970	0.922	0.922	0.930	0.955	4.96%	4.96%	4.08%	1.55%
Jan-20	0.900	0.931	0.930	0.940	0.957	3.45%	3.38%	4.48%	6.39%
Feb-20	0.960	0.940	0.939	0.950	0.960	2.04%	2.19%	1.01%	0.00%
					MAPE	4.22%	4.22%	4.10%	**3.78%**

H. KPI-8: Order Lead Time (Days)

Period	Actual	Forecasted				Absolute Relative Error			
		GM (1, 1)	DGM (1, 1)	GAGM (1, 1)	PSOGM (1, 1)	GM (1, 1)	DGM (1, 1)	GAGM (1, 1)	PSOGM (1, 1)
Sep-19	88	88.00	88.00	88.00	88.00	0.00%	0.00%	0.00%	0.00%
Oct-19	92	90.60	90.74	90.12	90.68	1.52%	1.37%	2.05%	1.44%
Nov-19	90	90.80	90.87	90.24	90.00	0.89%	0.97%	0.27%	0.00%
Dec-19	85	91.00	91.00	90.37	89.33	7.06%	7.06%	6.32%	5.09%
Jan-20	100	91.20	91.13	90.50	88.66	8.80%	8.87%	9.50%	11.34%
Feb-20	88	91.40	91.26	90.62	88.00	3.86%	3.70%	2.98%	0.00%
					MAPE	3.69%	3.66%	3.52%	**2.98%**

I. KPI-9: Downtime to Operating Time Ratio

Period	Actual	Forecasted				Absolute Relative Error			
		GM (1, 1)	DGM (1, 1)	GAGM (1, 1)	PSOGM (1, 1)	GM (1, 1)	DGM (1, 1)	GAGM (1, 1)	PSOGM (1, 1)
Sep-19	0.022	0.022	0.022	0.022	0.022	0.00%	0.00%	0.00%	0.00%
Oct-19	0.037	0.037	0.037	0.037	0.037	1.06%	0.73%	0.00%	0.00%
Nov-19	0.032	0.034	0.034	0.034	0.035	5.58%	5.76%	6.84%	7.84%
Dec-19	0.035	0.031	0.031	0.032	0.032	10.90%	10.91%	9.74%	8.04%
Jan-20	0.025	0.029	0.029	0.029	0.030	15.13%	14.92%	16.75%	20.08%
Feb-20	0.028	0.027	0.026	0.027	0.028	5.12%	5.46%	3.68%	0.00%
					MAPE	6.30%	6.30%	6.17%	**5.99%**

J. KPI-10: On-time Delivery Percentage

Period	Actual	Forecasted				Absolute Relative Error			
		GM (1, 1)	DGM (1, 1)	GAGM (1, 1)	PSOGM (1, 1)	GM (1, 1)	DGM (1, 1)	GAGM (1, 1)	PSOGM (1, 1)
Sep-19	96	96.00	96.00	96.00	96.00	0.00%	0.00%	0.00%	0.00%
Oct-19	99	98.60	98.62	98.79	99.00	0.40%	0.39%	0.21%	0.00%
Nov-19	97	98.20	98.21	98.40	98.75	1.24%	1.24%	1.44%	1.80%
Dec-19	100	97.80	97.80	98.00	98.50	2.20%	2.20%	2.00%	1.50%
Jan-20	95	97.40	97.39	97.61	98.25	2.52%	2.52%	2.75%	3.42%
Feb-20	98	97.00	96.99	97.22	98.00	1.02%	1.03%	0.79%	0.00%
					MAPE	1.23%	1.23%	1.20%	**1.12%**

K. KPI-11: Cost per Order ($)

Period	Actual	Forecasted				Absolute Relative Error			
		GM (1, 1)	DGM (1, 1)	GAGM (1, 1)	PSOGM (1, 1)	GM (1, 1)	DGM (1, 1)	GAGM (1, 1)	PSOGM (1, 1)
Sep-19	173.71	173.71	173.71	173.71	173.71	0.00%	0.00%	0.00%	0.00%
Oct-19	317.43	256.55	263.47	248.32	131.67	19.18%	17.00%	21.77%	58.52%
Nov-19	145.25	225.00	227.16	217.97	145.25	54.90%	56.39%	50.07%	0.00%
Dec-19	183.00	197.33	195.85	191.33	160.23	7.83%	7.02%	4.55%	12.44%
Jan-20	168.00	173.06	168.85	167.95	176.76	3.01%	0.51%	0.03%	5.22%
Feb-20	195.00	151.77	145.58	147.43	195.00	22.17%	25.35%	24.40%	0.00%
					MAPE	17.85%	17.71%	16.80%	**12.70%**

L. KPI-12: Carrying Cost of Inventory ($)

Period	Actual	Forecasted				Absolute Relative Error			
		GM (1, 1)	DGM (1, 1)	GAGM (1, 1)	PSOGM (1, 1)	GM (1, 1)	DGM (1, 1)	GAGM (1, 1)	PSOGM (1, 1)
Sep-19	6150	6150.00	6150.00	6150.00	6150.00	0.00%	0.00%	0.00%	0.00%
Oct-19	6500	6235.73	6248.82	6266.75	6404.00	4.07%	3.86%	3.59%	1.48%
Nov-19	6000	6239.86	6246.41	6277.38	6402.00	4.00%	4.11%	4.62%	6.70%
Dec-19	6400	6244.00	6243.99	6288.03	6400.00	2.44%	2.44%	1.75%	0.00%
Jan-20	5600	6248.13	6241.58	6298.70	6398.00	11.57%	11.46%	12.48%	14.25%
Feb-20	6720	6252.27	6239.17	6309.38	6396.01	6.96%	7.16%	6.11%	4.82%
					MAPE	4.84%	4.84%	4.76%	**4.54%**

M. KPI-13: Labor Cost ($)

Period	Actual	Forecasted				Absolute Relative Error			
		GM (1, 1)	**DGM (1, 1)**	**GAGM (1, 1)**	**PSOGM (1, 1)**	**GM (1, 1)**	**DGM (1, 1)**	**GAGM (1, 1)**	**PSOGM (1, 1)**
Sep-19	10100	10100.00	10100.00	10100.00	10100.00	0.00%	0.00%	0.00%	0.00%
Oct-19	9375	9546.61	9567.81	9396.10	9375.00	1.83%	2.06%	0.23%	0.00%
Nov-19	10688	9749.95	9761.39	9587.83	9498.37	8.78%	8.67%	10.29%	11.13%
Dec-19	9125	9957.62	9958.89	9783.48	9623.36	9.12%	9.14%	7.22%	5.46%
Jan-20	9750	10169.72	10160.38	9983.11	9750.00	4.30%	4.21%	2.39%	0.00%
Feb-20	10875	10386.33	10365.95	10186.82	9878.30	4.49%	4.68%	6.33%	9.17%
					MAPE	4.76%	4.79%	4.41%	**4.29%**

Table 5.3: Summary of the MAPE for the simulation of each warehouse [A-C].

A. MAPE for Best Shirt Ltd.

SL	KPIs	MAPE			
		GM (1, 1)	**DGM (1, 1)**	**GAGM (1, 1)**	**PSOGM (1, 1)**
1	Inventory Turnover	4.74%	4.74%	4.52%	4.12%
2	Inventory to Sales Ratio	7.59%	7.78%	7.40%	6.85%
3	Store Utilization	2.41%	2.41%	2.28%	2.27%
4	Orders per hour	4.45%	4.43%	4.18%	3.86%
5	Inventory Accuracy	2.09%	2.09%	2.00%	1.60%
6	Stock-out Percentage	8.07%	8.09%	6.38%	6.30%
7	Perfect Order Rate	4.22%	4.22%	4.10%	3.78%
8	Order Lead Time	3.69%	3.66%	3.52%	2.98%
9	Downtime to Operating Time Ratio	6.30%	6.30%	6.17%	5.99%
10	On-time Delivery Percentage	1.23%	1.23%	1.20%	1.12%
11	Cost per Order ($)	17.85%	17.71%	16.80%	12.70%
12	Carrying Cost of Inventory ($)	4.84%	4.84%	4.76%	4.54%
13	Labor Cost ($)	4.76%	4.79%	4.41%	4.29%

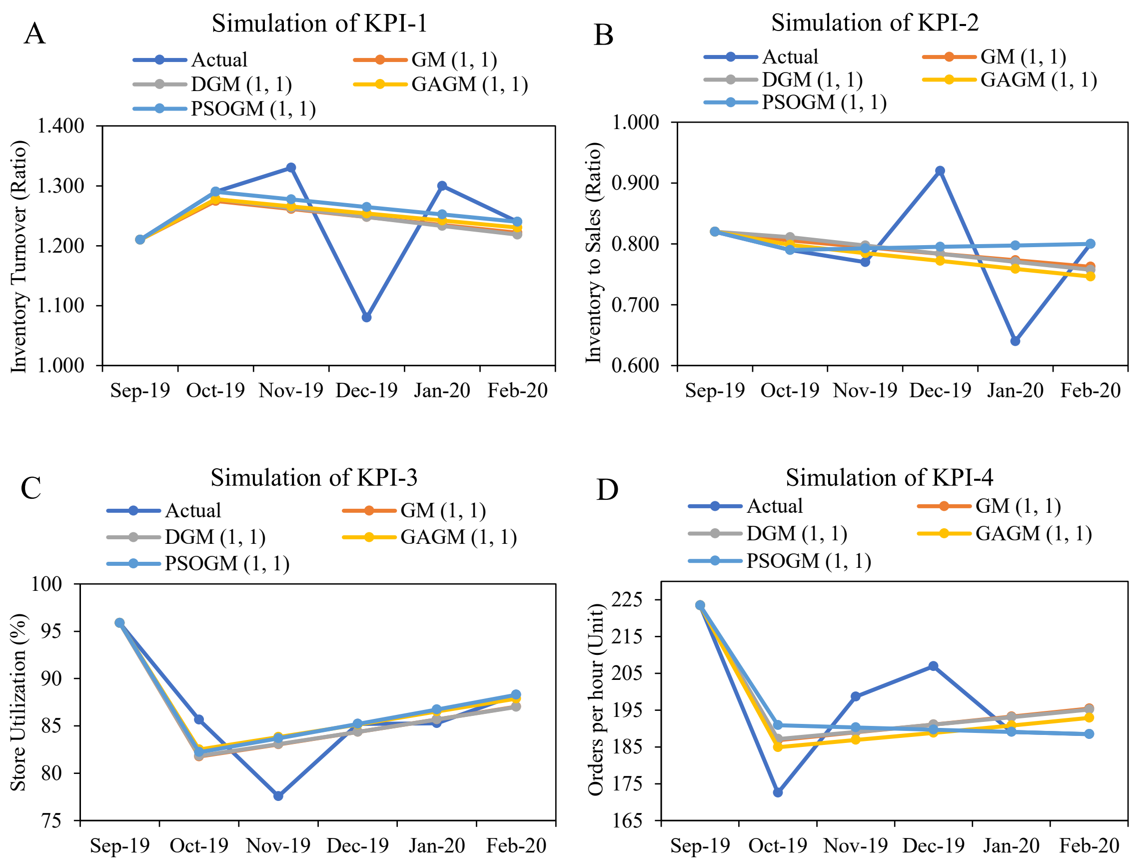
B. MAPE for Ever Smart Bangladesh Ltd.

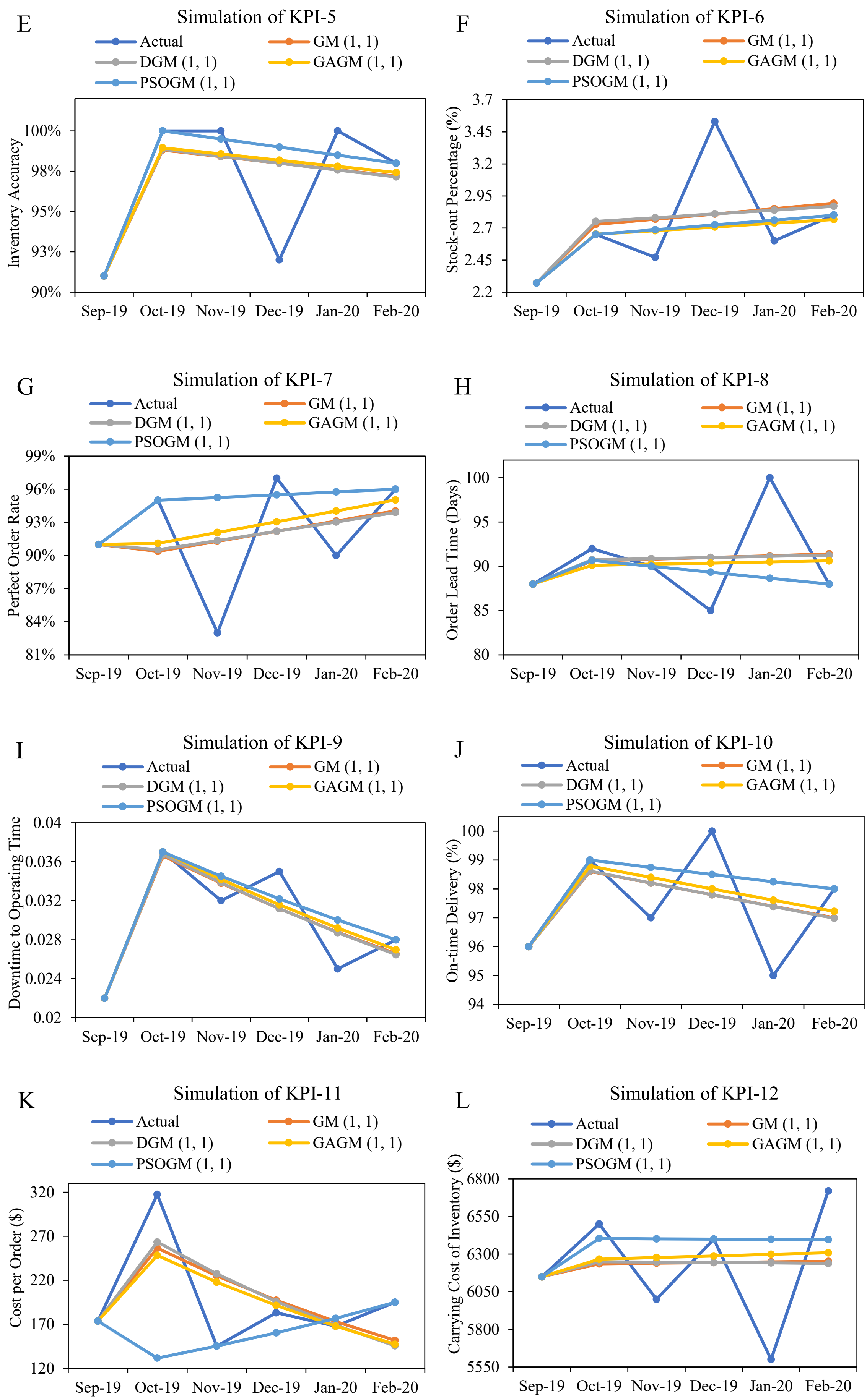
SL	KPIs	MAPE			
		GM (1, 1)	**DGM (1, 1)**	**GAGM (1, 1)**	**PSOGM (1, 1)**
1	Inventory Turnover Ratio	8.88%	8.98%	8.55%	7.58%
2	Inventory to Sales Ratio	9.93%	10.06%	9.74%	8.63%
3	Store Utilization (%)	4.45%	4.44%	4.36%	4.27%
4	Orders per hour (Number)	7.82%	7.74%	7.59%	7.56%
5	Inventory Accuracy (%)	1.22%	1.22%	1.20%	1.16%
6	Perfect Order Rate	3.85%	3.85%	3.79%	3.76%

7	Order Lead Time (Days)	5.70%	5.69%	5.38%	4.95%
8	Downtime to Operating Time Ratio	8.50%	8.56%	8.22%	5.97%
9	On-time Delivery Percentage	1.09%	1.09%	1.04%	1.02%
10	Cost per Order ($)	9.49%	9.63%	9.28%	8.01%
11	Labor Cost ($)	3.17%	3.18%	3.16%	3.08%

C. MAPE for Brothers Furniture Ltd.

		MAPE			
SL	**KPIs**	**GM (1, 1)**	**DGM (1, 1)**	**GAGM (1, 1)**	**PSOGM (1, 1)**
1	Inventory Turnover Ratio	11.73%	11.76%	11.58%	11.49%
2	Inventory to Sales Ratio	11.51%	11.71%	11.29%	9.92%
3	Store Utilization (%)	4.44%	4.44%	4.33%	4.31%
4	Rate of Return Ratio	13.35%	13.59%	13.01%	12.15%
5	Orders per hour (Number)	17.65%	18.48%	16.12%	15.97%
6	Inventory Accuracy (%)	0.47%	0.47%	0.46%	0.42%
7	Damaged Inventory (%)	15.51%	15.72%	13.71%	12.80%
8	Perfect Order Rate	5.89%	5.89%	5.69%	5.39%
9	Order Lead Time (Days)	4.83%	4.81%	4.59%	4.53%
10	Downtime to Operating Time Ratio	10.28%	10.46%	10.19%	8.71%
11	On-time Delivery Percentage	9.98%	10.06%	8.79%	8.53%
12	Carrying Cost of Inventory ($)	2.46%	2.46%	2.43%	2.04%
13	Labor Cost ($)	6.87%	6.93%	6.73%	6.18%




E
Simulation of KPI-5
Actual
GM (1, 1)
DGM (1, 1)
GAGM (1, 1)
PSOGM (1, 1)
Inventory Accuracy
100%
98%
95%
93%
90%
Sep-19
Oct-19
Nov-19
Dec-19
Jan-20
Feb-20
F
Simulation of KPI-6
Actual
GM (1, 1)
DGM (1, 1)
GAGM (1, 1)
PSOGM (1, 1)
Stock-out Percentage (%)
3.7
3.45
3.2
2.95
2.7
2.45
2.2
Sep-19
Oct-19
Nov-19
Dec-19
Jan-20
Feb-20
G
Simulation of KPI-7
Actual
GM (1, 1)
DGM (1, 1)
GAGM (1, 1)
PSOGM (1, 1)
Perfect Order Rate
99%
96%
93%
90%
87%
84%
81%
Sep-19
Oct-19
Nov-19
Dec-19
Jan-20
Feb-20
H
Simulation of KPI-8
Actual
GM (1, 1)
DGM (1, 1)
GAGM (1, 1)
PSOGM (1, 1)
Order Lead Time (Days)
100
95
90
85
80
Sep-19
Oct-19
Nov-19
Dec-19
Jan-20
Feb-20
I
Simulation of KPI-9
Actual
GM (1, 1)
DGM (1, 1)
GAGM (1, 1)
PSOGM (1, 1)
Downtime to Operating Time
0.04
0.036
0.032
0.028
0.024
0.02
Sep-19
Oct-19
Nov-19
Dec-19
Jan-20
Feb-20
J
Simulation of KPI-10
Actual
GM (1, 1)
DGM (1, 1)
GAGM (1, 1)
PSOGM (1, 1)
On-time Delivery (%)
100
99
98
97
96
95
94
Sep-19
Oct-19
Nov-19
Dec-19
Jan-20
Feb-20
K
Simulation of KPI-11
Actual
GM (1, 1)
DGM (1, 1)
GAGM (1, 1)
PSOGM (1, 1)
Cost per Order ($)
320
270
220
170
120
Sep-19
Oct-19
Nov-19
Dec-19
Jan-20
Feb-20
L
Simulation of KPI-12
Actual
GM (1, 1)
DGM (1, 1)
GAGM (1, 1)
PSOGM (1, 1)
Carrying Cost of Inventory ($)
6800
6550
6300
6050
5800
5550
Sep-19
Oct-19
Nov-19
Dec-19
Jan-20
Feb-20

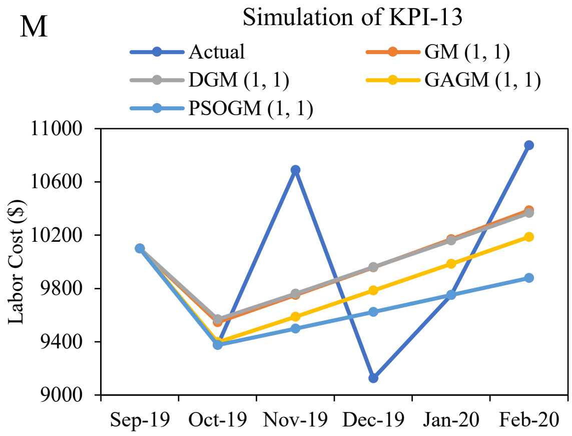
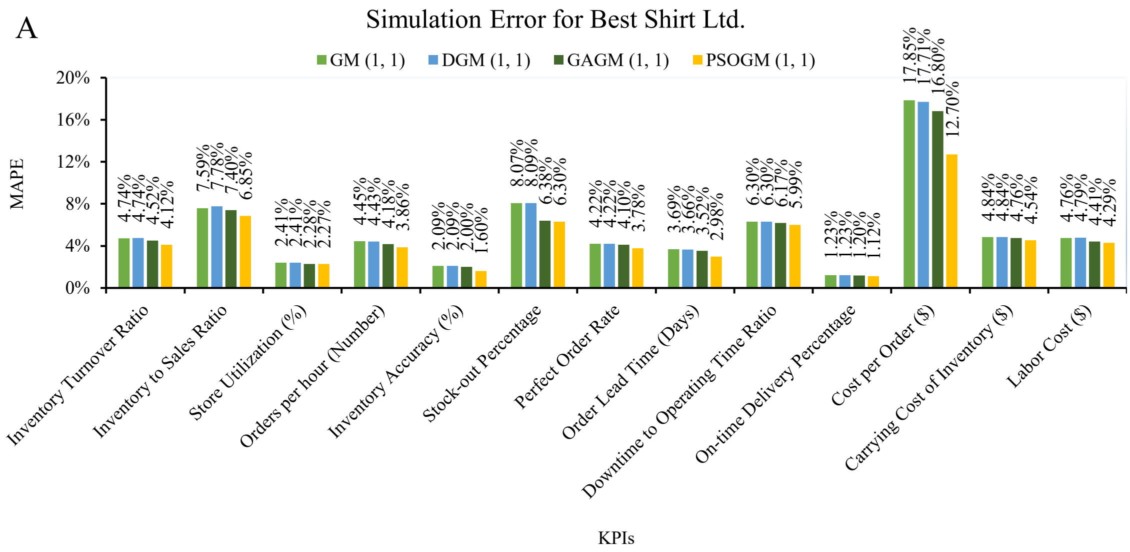
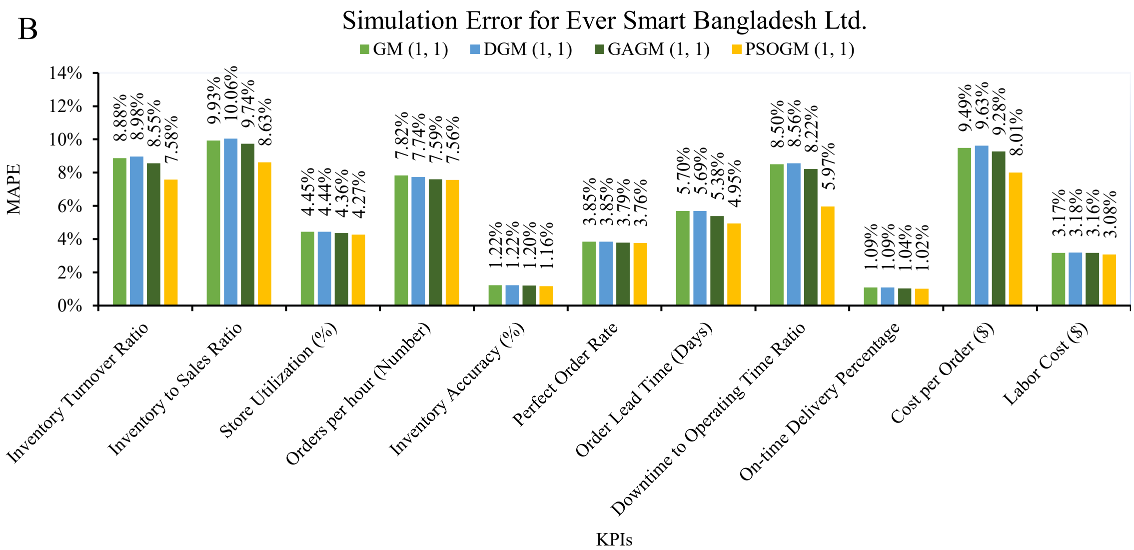


Figure 5.1: Illustration of the actual data with the forecasted values of available 13 KPIs of Best Shirt Limited [A-M].





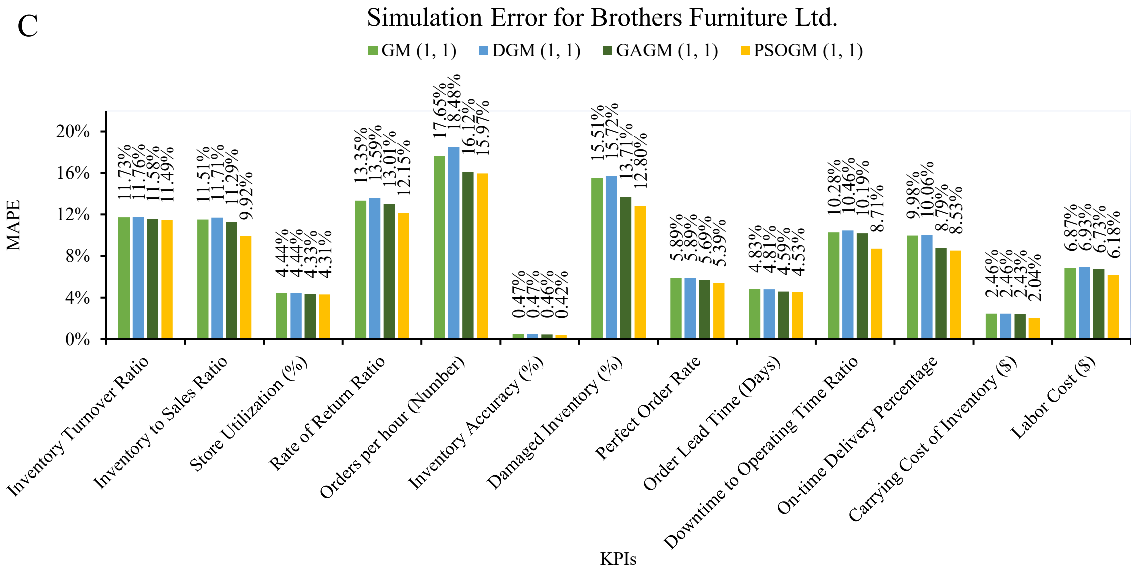


Figure 5.2: Illustration of the summary of the simulation error generated by the considered grey models for the three selected warehouses [A-C].

Figure 5.1 indicates that the forecasted line of the proposed model fits well with the actual data for the warehouse of Best Shirt Ltd. But in the second data point of the KPI-11, the deviation is higher than the other three models though the overall mean deviation is less. According to the above Table 5.3 and Figure 5.2, it is evident that the prediction performance of the proposed grey model, PSOGM (1, 1), is better than the other three grey models for all the selected KPIs of the warehouses of the three industries. In the remaining three models, the GAGM (1, 1) model performs better than the other two models. The performance of the two basic grey models, GM (1, 1) and DGM (1, 1), is almost identical for all the KPIs and somewhat better the performance of GM (1, 1) than DGM (1, 1). Overall, from the above analysis of the forecasting accuracy of the four grey models, the PSOGM (1, 1) model outperforms the others; it is used for the prediction of the selected KPIs over the next five months from the end period of the actual data for Best Shirt Ltd., which is shown in Table 5.4.

Table 5.4: Prediction of each KPI for the Best Shirt Ltd. warehouse over the next five months.

SL	KPIs	Forecasted				
		Mar-20	Apr-20	May-20	Jun-20	Jul-20
1	Inventory Turnover	1.228	1.216	1.204	1.192	1.180
2	Inventory to Sales Ratio	0.803	0.805	0.808	0.810	0.813
3	Store Utilization	89.85	91.460	93.100	94.770	96.470
4	Orders per hour	187.91	187.330	186.740	186.160	185.580

5	Inventory Accuracy	0.975	0.970	0.965	0.960	0.956
6	Stock-out Percentage	2.84	2.88	2.92	2.96	3.00
7	Perfect Order Rate	0.963	0.965	0.968	0.970	0.973
8	Order Lead Time	87.34	86.69	86.04	85.40	84.76
9	Downtime to Operating Time Ratio	0.026	0.024	0.023	0.021	0.020
10	On-time Delivery Percentage	97.75	97.50	97.26	97.01	96.76
11	Cost per Order ($)	215.12	237.31	261.79	288.8	318.59
12	Carrying Cost of Inventory ($)	6252.88	6204.59	6156.68	6109.14	6061.96
13	Labor Cost ($)	10008.30	10140.00	10273.44	10408.63	10545.60

5.3 Weight Calculation of KPIs

Since the importance of each KPI is unequal, hence their effect to the OWP will also unequal. In this study, unweighted KPIs data from the warehouse of the Best Shirt Ltd. has been collected to measure the cumulative performance of that warehouse. The weight of each KPI is required to measure the performance of the warehouse accurately. To determine the global weight of each KPI, this study employs the AHP method; the final KPI scores are shown in Table 5.5. This table presents the most significant category of KPIs over the others based on the pairwise comparison matrices for six experts, which are displayed in (Appendix-D with Tables D1- D5). Based on Table 4.1 and Table 5.1, Figure 5.3 illustrates the AHP model for the Best Shirt Ltd.

Table 5.5: Local and global weights of each KPI for the warehouse of Best Shirt Ltd.

Category	Local Weight	KPI	Symbol	Local Weight	*Global Weight, W_i
Productivity	29.0%	Inventory Turnover	KPI_1	57.5%	16.68%
		Inventory to Sales Ratio	KPI_2	8.0%	2.32%
		Store Utilization	KPI_3	12.7%	3.68%
		Orders per hour	KPI_4	21.8%	6.32%
Quality	43.7%	Inventory Accuracy	KPI_5	66.5%	29.06%
		Stock-out Percentage	KPI_6	23.1%	10.09%
		Perfect Order Rate	KPI_7	10.4%	4.54%
Time	17.0%	Order Lead Time	KPI_8	72.4%	12.31%
		Downtime to Operating Time Ratio	KPI_9	19.3%	3.28%
		On-time Delivery Percentage	KPI_{10}	8.3%	1.41%
Cost	10.3%	Cost per Order	KPI_{11}	51.1%	5.26%
		Carrying Cost of Inventory	KPI_{12}	10.0%	1.03%
		Labor Cost	KPI_{13}	38.9%	4.01%
		Total			**100%**

* W_i = *Local Weight of Category* × *Local Weight of each KPI.*

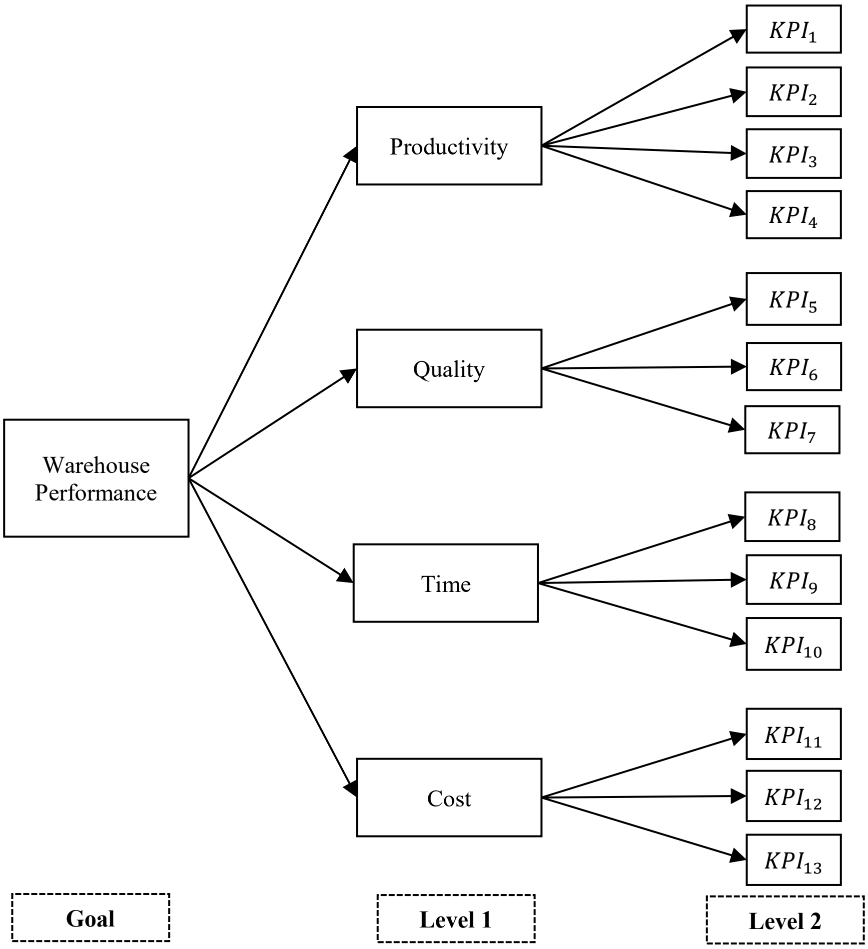


Figure 5.3: The AHP model available KPIs of Best Shirt Ltd.

According to the above Table 5.5, the global weight of each KPI is obtained by multiplying the local importance of each KPI by the local significance of the corresponding KPI category. The table illustrates that, among the four groups, the local importance is highest for the second category, "Quality". This suggests that the industry is most concerned with the quality of service and production. Among all the KPIs, KPI_1 (Inventory Turnover) and KPI_{11} (Cost Per Order) achieve the highest and lowest global weights, respectively.

5.4 Performance Prediction

The overall performance of the warehouse, $\eta_{Warehouse}$ for the selected garments industry is measured through the following equation.

$$\eta_{Warehouse} = \sum_{i=1}^{n} (W_i \times KPI_i) \tag{5.1}$$

Where, W_i indicates the global weights of each KPI, which are obtained from Table 5.4. The KPIs' values are not directly applicable to measure the performance. Before applying this formula to calculate the overall performance, the forecasted values of the KPIs need to convert as the normalized values. The normalization is done in the range of [0.7 to 1.0] using the following equation:

$$Normalization = l + \frac{(X-L)(m-l)}{(M-L)} \tag{5.2}$$

Where l is the minimum value of the desired range, here 0.70 and m is the maximum of the desired range, here 1.00. The X indicates the values that have to be normalized. The L and M indicate the minimum and maximum values of the data, respectively, that have to be normalized, respectively. Finally, applying equation (5.1) and equation (5.2), overall performance of the warehouse of the Best Shirt Ltd. is measured using the normalized KPI values, which are also presented in Table 5.6. A graphical illustration is also shown in Figure 5.4; this illustrates the dominant trend by utilizing the measured overall performance.

Table 5.6: Overall warehouse performance prediction through normalized-forecasted KPIs values for the Best Shirt Ltd.

Indicators	Sym bol	Global Weight, W_i	Normalized forecasted KPIs value				
			Mar-20	**Apr-20**	**May-20**	**Jun-20**	**Jul-20**
Inventory Turnover	KPI_1	16.68%	0.934	0.898	0.862	0.826	0.790
Inventory to Sales Ratio	KPI_2	2.32%	0.803	0.805	0.808	0.810	0.813
Store Utilization	KPI_3	3.68%	0.899	0.915	0.931	0.948	0.965
Orders per hour	KPI_4	6.32%	0.937	0.920	0.902	0.885	0.867
Inventory Accuracy	KPI_5	29.06%	0.975	0.970	0.965	0.960	0.956
Stock-out Percentage	KPI_6	10.09%	0.757	0.753	0.750	0.746	0.743
Perfect Order Rate	KPI_7	4.54%	0.963	0.965	0.968	0.970	0.973
Order Lead Time	KPI_8	12.31%	0.814	0.842	0.870	0.897	0.925
Downtime to Operating Time Ratio	KPI_9	3.28%	0.961	0.964	0.966	0.969	0.970
On-time Delivery Percentage	KPI_{10}	1.41%	0.978	0.975	0.973	0.970	0.968
Cost per Order	KPI_{11}	5.26%	0.902	0.869	0.832	0.792	0.747
Carrying Cost of Inventory	KPI_{12}	1.03%	0.812	0.819	0.826	0.834	0.841
Labor Cost	KPI_{13}	4.01%	0.848	0.815	0.782	0.748	0.714
Overall Performance, $\eta_{Warehouse}$ =			**90.55%**	**89.79%**	**89.00%**	**88.19%**	**87.38%**

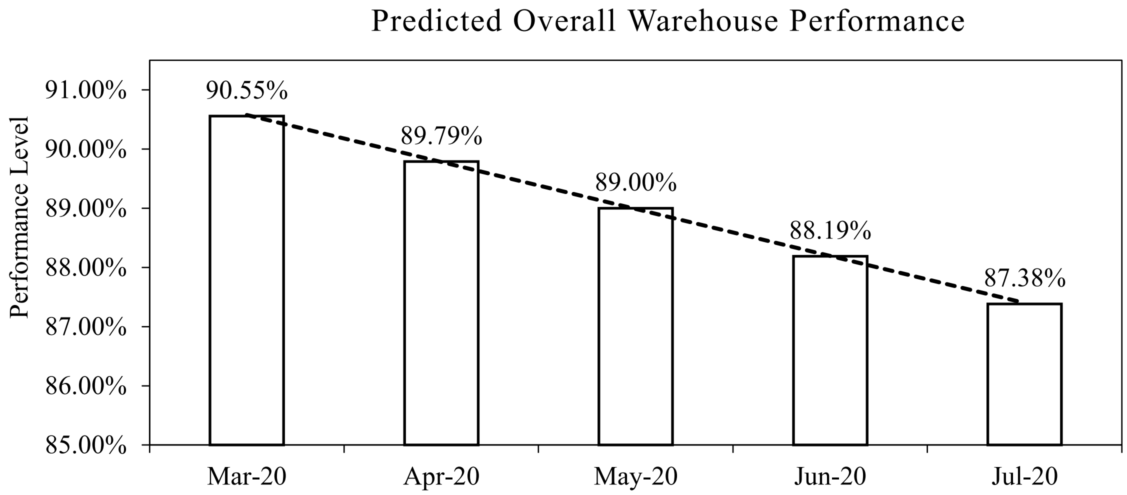


Figure 5.4: Forecasted overall warehouse performance of Best Shirt Ltd.

In Table 5.5, the overall performance of the warehouse of the Best Shirt Ltd. is measured from the forecasted normalized value for the five consecutive months from March 2020 to July 2020. The score of the overall performance of the indicates a decreasing pattern that deviates from the desired performance of 90. The final result entirely depends on the amount of the forecasted KPIs data and its global weights obtained from the AHP process. One partial cause may be responsible for the small deviation is the randomness of the raw data is very low, which produces less variability in the future trend of the forecasting. And in the case of weight of the KPI, the result may affect in less if high importance is achieved by those KPIs, which are changed minutely in the future.

Finally, there has been a decline in warehouse performance, indicating that the manager should take diagnostic action in advance. The manager can take corrective measures for the KPIs that have a high impact on overall performance according to their weight. Such measures may entail reallocating resources, capital or workers—or even redesigning the warehouse's operational systems.

CHAPTER 6
CONCLUSION AND RECOMMENDATION

6.1 Conclusion

This study contributes to the improvement of the prediction accuracy of the GM (1, 1) model, incorporating the PSO algorithm to minimize the development coefficients of the grey model. The proposed model is named as PSOGM (1, 1) is used to predict the overall performance of the warehouse of an RMG industry of Bangladesh utilizing the major KPIs of that warehouse. The performance of the PSOGM (1, 1) has been compared against three other grey models namely GAGM (1, 1), DGM (1, 1), and GM (1, 1) models, and the evaluation index MAPE is used to validate the performance of the integrated models. The primary findings of the study can be summarized as follow:

- Designed robust parameters for PSO and GA using the Taguchi process for increasing the search efficiency of the hybrid grey model based on the MAPE as a minimizing objective function.
- Identified sixteen major KPIs for the warehouses of three different industries of Bangladesh and among them available KPIs are ranked through the AHP method for a specific warehouse, which is a Bangladeshi RMG warehouse. The overall warehouse performance of that warehouse is measured using forecasted values of each KPIs obtained from the proposed model.
- Finally, the proposed model shows promising results against the other grey models. It reduces the MAPE $6\% - 29\%$ for the selected KPIs of the three warehouses and $23\% - 28\%$ for the pilot data series than the MAPE of the GM (1, 1), GAGM (1, 1), and DGM (1, 1), models. This performance index showed that the PSOGM (1, 1) model outperformed the other grey models and it indicates the robustness of the models.

Eventually, the findings and developed models can help the warehouse professionals and managers to make a quick estimation of warehouse KPIs which will help to measure the overall warehouse performance ahead in time to sidestep the massive losses.

6.2 Recommendation

This study only considers MAPE criteria for the error analysis and is also used as the objective function for the PSO and GA. But there are more other methods to analyze the forecasting error, which may consider all together as multiple objective functions for the optimization algorithms as multi-objective optimization. So future studies can get a more accurate result than the current method.

Finally, this study can provide mathematical support to design the performance dashboard for the warehouse as well to industry for smart manufacturing system by the integration of the Internet of Things (IoT) into the warehousing system where data analysis and prediction is required.

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APPENDICES

Appendix A. Summary of the Literature Review for the GM (1, 1) model.

Table A1: Summary of the literature of the application, improvement of GM (1, 1) model.

Authors	Contribution	Method	Error Analysis	Case Country
(Hsu & Chen, 2003)	• Design improved grey GM (1,1) model, using residual modification with artificial neural network • Optimized Parameter: background value, α	GM (1,1) ANN	MAPE	Power demand forecasting of Taiwan
(Tien, 2009)	• Develop new grey model first entry grey model, FGM (1, 1) • Optimized Parameter: background value, α	GM (1, 1) FGM (1, 1)	MAPE	The tensile strength and failure time prediction of materials
(Zhou et al., 2009)	• Nonlinear grey Bernoulli model (NGBM) is proposed combining GM (1,1) with the Bernoulli differential equation and optimized the parameter of the proposed model by PSO • Optimized Parameter: background value, α	GM (1,1) PSO	MAPE	Power load forecasting of Hubei (sample 1996 to 2007)
(Z. Wang et al., 2009)	• Improved GM (1, 1) model through non-homogeneous exponential law to fit the accumulated sequence of the grey model • Optimized Parameter: background value, α	GM (1,1) Use the integral formula for background value	MAPE	Financial investment in S&T (1998 to 2002 is simulated and 2003 and 2004 is the prediction)
(Lee & Tong, 2011)	• Design improved grey GM (1,1) model, using GA • Optimized Parameter: background value, α	GM (1,1) GA	MAPE	Annual energy consumption of China (1990 to 2007)
(D. Ma et al., 2011)	• Underground pressure forecasting by developing improved GM (1, 1) model trough parameter optimization of the GM (1, 1) model • Optimized Parameter: background value, α	GM (1,1) PSO	MAPE MAD TIC	Data of UPWS of S5-6 working surface' first station of Changchun coal mine in China in June 2010
(Qian et al., 2011)	• Developing improved PSO based GM (1,1) Power model • Optimized Parameter: background value, α and c (another background parameter of power model)	GM (1,1) Power model PSO	MAPE	Road traffic accidents in China during the period of 1990-2009
(W. Ma et al., 2013)	• Introduce a high-precision hybrid model based on grey prediction and rolling mechanism optimized PSO • Optimized Parameter: background value, α (here termed as λ)	GM (1,1) PSO Rolling GM (1, 1)	MAPE	China' iron ore import and consumption, Statistical Yearbook (1996–2011)
(Cao et al., 2014)	• Optimizing the background value and initial item • Optimized Parameter: background value, α and initial value of the time response function	GM (1,1) The integral formula for background value	MAPE	Numerical data sequence (source unknown)
(Lai et al., 2015)	• Design an improved grey model based on neural networks to better predict market demand after transportation disruption • Divide the original data sequence into n − 3 sub-sequences and choose the best series for future prediction	GM (1, 1) ANN	MAPE	Weekly effective sales (units) between 1st January and 30th March in HX factory
(Ying et al., 2015)	• Develop an optimized grey model • Optimized Parameter: background value, α and initial value of the time response function	GM (1, 1) function transformation	MAPE	Prediction of bearing sleeve wear
(Madhi & Mohamed, 2016)	• Develop an optimized grey model • Optimized Parameter: background value, α	GM (1, 1) The integral formula for background value	MAPE	A sequence of $f(t) = 2e^{0.4t}, t = 1,2,\ldots,15$ is used

(Zhao et al., 2016)	• Develop an optimized grey model with Rolling Mechanism • Optimized Parameter: development coefficients a and b	GM (1, 1) MFO	MAPE	Electricity consumption (2001 to 2009) of Inner Mongolia
(Kewen Li et al., 2016)	• Develop an optimized grey model • Optimized Parameter: development coefficients a [-0.5, 0.5] and $b \in ([\min(a * x^{(1)}(k-1) + x^{(0)}(k)),\ \max(a * x^{(1)}(k) + x^{(0)}(k))],\ k = 1, 2, 3, \dots\dots\dots, n.)$	GM (1, 1) PSO	MAPE MSE MAE	Traffic data of the UK academic network backbone (19 Nov. 2004, 09:30 a.m. to 27 Jan. 2005, 11:11 a.m.)
(Hu & Jiang, 2017)	• Develop the neural-network-based GM (1,1) model based on residual modification • Optimized Parameter: development coefficients a and b	GM (1, 1) ANN Residual model	MAPE	annual electricity demand (1981–2002) of China, collected from China Statistical Yearbook (2014)
(Xu et al., 2017)	• Introduce improved-time-response grey prediction model • Optimized Parameter: parameters of the TRF	GM (1, 1) IRGM (1, 1) PSO	MAPE	Data of electricity consumption in China(2000e2012)
(Meng et al., 2017)	• Improved GM (1,1) Based on PSO with Stochastic Weight • Optimized Parameter: development coefficients a and b	GM (1, 1) PSO	MAPE	Low rising and high rising data series (5 samples)
(Hao et al., 2018)	• Design hybrid grey model based on ANN optimized by PSO • Optimized Parameter: parameter of ANN	GM (1, 1) ANN PSO	MAPE MAD TIC	End-of-life vehicles recycled in Shanghai during (2005- 2016)
(Z. X. Wang et al., 2018)	• Develop a seasonal GM (1,1) model based on • Optimized Parameter: background value, α	GM (1, 1) SGM (1, 1) PSO	MAPE RMSE MAE	Seasonal electricity consumption of China's primary industries (2010 to 2016)
(Ding et al., 2018)	• Develop a novel optimized GM (1, 1) model combining initial condition and rolling mechanism • Optimized Parameter: background value, α and initial value	GM (1, 1) GM (1, 1, $x^{(1)}(n)$) PSO	MAPE RMSE	Projecting China's total electricity consumption (sample use 2005 - 2014)
(Zeng et al., 2020)	• Develop a new grey model based on interval grey number • Optimized Parameter: development coefficients, b	GM (1, 1) Interval grey number	Rationality analysis of simulation	China's total natural gas consumption (TC) in 2009–2018
(Ervural & Ervural, 2018)	• Propose an optimal grey model based on PSO and GA • Optimized Parameter: development coefficients, a and b	GM (1, 1) PSO GA	MAPE RMSE	Annual electricity consumption of Turkey (1996 and 2016)
(Z. X. Wang & Li, 2019)	• Develop a grey Verhulst model based on PSO • Optimized Parameter: development coefficients, a and b	GM (1, 1) DNE-grey Verhulst PSO	MAPE RMSE MAE	CO_2 emissions per capita from 1990 to 2014 in China

** All abbreviations are defined in 'List of Abbreviations'.*

Appendix B. MATLAB Code of PSOGM (1,1) Forecasting Method.

The following MATLAB code is constructed for the proposed model to simulate and predict the future and also used to analyze the forecasting error.

```
clc;
clear;
close all;
global y;
y = input ('Please input data on hand in matrix format  ');

%% Calculation of the range of the parameter b
W=zeros (3,1);
Q=zeros (3,1);
m=0;
for w = 0:.5:1
% Input of on hand data and formation of matrix
%y= input ('Please input data on hand in matrix format  ');
%y= [60.7 73.8 86.2 100.4 123.3];
n=length(y);
yy=ones(n,1);
yy(1)=y(1);
% Calculations of AGO
for i=2:n
yy(i)=yy(i-1)+y(i);
end

%Mean sequance generation
B=ones(n-1,2);
for i=1:(n-1)
B(i,1)=-(w*yy(i)+(1-w)*yy(i+1));
end
BT=B';
YN = ones(n-1,1);
for j=1:n-1
YN(j)=y(j+1);
end

%Solution of the matrix and calculation of a, b & t
A=(BT*B)\(BT*YN);
m=m+1;
Q(m) = A(1);
W (m) = A(2);
end
e= min(Q);
f= max(Q);
c= min(W);
d= max(W);

%% Problem Definition
CostFunction = @MAPE; % Cost Function
nVar = 2;             % Number of Unknown (Decision) Variables
VarSize = [1 nVar];   % Matrix size of decision variables
VarMin =  [e c]      % Lower bound of decision variables
VarMax =  [f d]      % Upper bound of decision variables

%% Parameters of PSO
Wmax = 0.9;               % Inertia Coefficent Maximum Litmit
Wmin = 0.1;               % Inertia Coefficent Minimum Litmit
MaxIT = 300; %input('Maximum Iteration (MaxIT)     = ');   % Maximum numer of iterations
nPop = 50;  %input ('Population Size (npop)        = ');   % Population size or Swarm
size
C1 = 1.5; %input   ('Acceleration Coefficient (C1) = ');   % Personal Accelaration
Coefficient
C2 = 1.5; %input   ('Acceleration Coefficient (C2) = ');   % Social (Global) Accelaration
Coefficient
eqn= 2; %input   ('Inertia Weight Equation No    = ');   % Inertia Equation
%% Initialization

% The particle template
empty_particle.Position = [];
empty_particle.Velocity = [];
empty_particle.Cost = [];
```

```
empty_particle.Best.Position = [];
empty_particle.Best.Cost = [];

% Creat Population array
particle = repmat(empty_particle, nPop, 1);

% Initialize Golobal Best
GlobalBest.Cost = inf;

% Initialize population member
for i=1:nPop
    % Generate random solution
    particle(i).Position = unifrnd (VarMin, VarMax, VarSize);

    %Initialize Velocities
    particle(i).Velocity = zeros (VarSize);

    %Evaluation
    particle(i).Cost = CostFunction (particle(i).Position);

    % Update personal Best
    particle(i).Best.Position = particle(i).Position;
    particle(i).Best.Cost = particle(i).Cost;

    % Update Global Best
    if particle(i).Best.Cost< GlobalBest.Cost
        GlobalBest = particle(i).Best;

    % Array to hold Best Cost on each iteration
     BestCosts = zeros(MaxIT, 1);
    end
end

%% Main Loop f PSO
for it=1:MaxIT
    if eqn == 1
    w= 0.7;
    end
    if eqn == 2
    w = Wmax-((Wmax-Wmin)/MaxIT *it);
    end
    if eqn == 3
    w= Wmin+(Wmax-Wmin)*0.95^(it-1);
    end
    if eqn == 4
    w= 0.5+rand()/2;
    end
    for i=1:nPop
    % Update Velocity
 particle(i).Velocity = w*particle(i).Velocity...
     + C1*rand(VarSize).*(particle(i).Best.Position - particle(i).Position)...
     + C2*rand(VarSize).*(GlobalBest.Position - particle(i).Position);

 % Update Position
 particle(i).Position = particle(i).Position + particle(i).Velocity;

 % Evaluation
 particle(i).Cost = CostFunction (particle(i).Position);

 % Update personal Best
 if particle(i).Cost < particle(i).Best.Cost
     particle(i).Best.Position = particle(i).Position;
     particle(i).Best.Cost = particle(i).Cost;

    % Update Global Best
    if particle(i).Best.Cost< GlobalBest.Cost
        GlobalBest = particle(i).Best;
    end
 end
    end
        % Store best cost value
    BestCosts(it) = GlobalBest.Cost;

    % Display Iteration Information
    %disp (['Iteration'  num2str(it) ': Best Cost ='  num2str(BestCosts(it))]);

end
```

```
%% Results

%figure;
%plot (BestCosts, 'Linewidth', 2);
%semilogy (BestCosts, 'Linewidth', 2);
%xlabel ('Iteration');
%ylabel ('BestCost');
%grid on;
GlobalBest;
GlobalBest.Position;

%%
z = GlobalBest.Position;
a = z(1);
b = z(2);
t=b/a;
%Time series equation and simulated or predicted data
%y=X;
n=length(y);
yys = ones (n,1);
yys (1) = y (1);
for i = 1:n-1
yys(i+1)=(y(1)-t)*(exp(-a*(i)))*(1-exp(a));
end

 % Error Analysis
 E = ones (n,1);
 RE = ones (n,1);
 sum = 0;
 for i = 1:n
E (i) = y (i) - yys (i);
RE (i) = ((abs(E (i))/y(i))*100);
sum = sum + RE (i);
 end
ARE = sum/(n);

fprintf ('Raw Data: \n');
y;
fprintf ('Predicted Data: \n');
yys;
fprintf ('Average relative error in percentage: \n');
ARE
```

The code for the objective function, “objFunction” that is called as MAPE at first of the iteration in the above program,

```
function z = MAPE(a)
global y; % Raw Data
n= length (y);
sum =0;
yy = ones (n,1);
yy (1) = y (1);
for i = 1:n-1
yy(i+1)=abs((y(1)-(a(2)/a(1)))*(exp(-a(1)*(i)))*(1-exp(a(1)))-y(i+1));

% Absolute Error Calculation
sum=sum+(yy(i+1)/y(i+1));
end
z = sum*100/(n-1); % Relative Error
end
```

Appendix C. Detailed Description of the Selected KPIs Data of the Three Companies.

Table C1: Necessary information about Best Shirt Ltd.

Company Information	
Factory	Best Shirts Ltd.
Address	35, Kunia, Borobari, National University-1704, Gazipur, Bangladesh
Business	Ready-Made Garments (Woven Shirts & Ladies Tops manufacturer)
Factory Capacity	6 Million pcs per Year
Factory Workforce	Approximated 2500 persons
Warehouse Information	
Data Collected from	Bonded Warehouse
Items	Single product (Fabrics)
Warehouse space capacity	6500 Sq. ft.
Warehouse capacity	17 Million of Yard fabrics.
Inventory system	Industrial Racking system
Staff	8
Workers	25

Table C2: Details of the raw data for the available KPIs of Best Shirt Ltd.

SL	**KPI**	**Sep-19**	**Oct-19**	**Nov-19**	**Dec-19**	**Jan-20**	**Feb-20**	**Standard of KPIs**		
								Max	**Target**	**Min**
1	Inventory Turnover	1.21	1.29	1.33	1.08	1.30	1.24	1.25	1.2	1.15
2	Inventory to Sales Ratio	0.82	0.79	0.77	0.92	0.64	0.8	1.00	0.8	0.7
3	Store Utilization	95.86	85.64	77.56	85.19	85.26	88.27	100	90	70
4	Orders per hour	223.45	172.5	198.62	206.9	189.09	188.5	190	185	180
5	Inventory Accuracy	0.91	1.00	1.00	0.92	1.00	0.98	1.00	1.00	0.7
6	Stock-out Percentage	2.27	2.65	2.47	3.53	2.60	2.80	0.00	1.75	3.50
7	Perfect Order Rate	0.91	0.95	0.83	0.97	0.90	0.96	1.00	0.98	0.70
8	Order Lead Time (Days)	88	92	90	85	100	88	83	87	90
9	Downtime to Operating Time Ratio	0.022	0.037	0.032	0.035	0.025	0.028	0.00	0.10	0.20
10	On-time Delivery Percentage	96	99	97	100	95	98	100	100	100
11	Cost per Order ($)	173.71	317.43	145.25	183	168	195	150	250	350
12	Carrying Cost of Inventory ($)	6150	6500	6000	6400	5600	6720	5000	6000	7000
13	Labor Cost ($)	10100	9375	10688	9125	9750	10875	9400	10000	10600

Table C3: Necessary information about Ever Smart Bangladesh Ltd.

Company Information	
Factory	Ever Smart Bangladesh Limited (A subsidiary of Crystal International Group)
Address	Begumpur, P.O: Bhabanipur, Hotapara, Gazipur-1740, Bangladesh
Business	Ready-Made Garments Manufacturing Company (Knit Items)
Factory Capacity (Pcs/Month)	650000
Factory Workforce	Approximated 1300 persons
Warehouse Information	
Data Collected from	Bonded Warehouse
Items	Knit Product (Fabrics & Trims)
Warehouse space capacity	4800 Sq. ft.
Warehouse capacity	168000 Yards Fabrics.
Inventory system	Industrial Racking system
Staff	8
Workers	30 (RM & FG WHS)

Table C4: Details of the raw data for the available KPIs of Ever Smart Bangladesh Limited.

SL	**KPI**	**Sep-19**	**Oct-19**	**Nov-19**	**Dec-19**	**Jan-20**	**Feb-20**	**Standard of KPIs**		
								Max	**Target**	**Min**
1	Inventory Turnover Ratio	1.042	1.376	1.557	1.213	1.157	1.513	1.5	1.35	1.1
2	Inventory to Sales Ratio	0.280	0.472	0.573	0.512	0.378	0.497	0.6	0.4	0.2
3	Store Utilization (%)	75	70	65	81	72	79	85	75	60
4	Orders per hour (Number)	0.067	0.097	0.070	0.089	0.100	0.094	0.2	0.1	0.05
5	Inventory Accuracy (%)	97	100	96	97	100	99	100	95	90
6	Perfect Order Rate	1	0.91	1	0.95	0.99	0.87	1	0.95	0.8
7	Order Lead Time (Days)	75	77	70	71	65	81	60	70	85
8	Downtime to Operating Time Ratio	0.050	0.070	0.065	0.055	0.072	0.045	0	0.1	0.2
9	On-time Delivery Percentage	100	97	95	100	99	98	100	100	100
10	Cost per Order ($)	128.57	250.45	190.78	175.98	225.89	205.63	120	200	300
11	Labor Cost ($)	9000	8845	9675	9500	8595	8930	8000	9000	10000

Table C5: Necessary information about Brothers Furniture Ltd.

Company Information	
Factory	Brothers Furniture Limited
Address	Horindhara, Tanari Mhor, Haymathpur, Saver, Bangladesh
Business	Furniture
Factory Capacity	1500 pcs per Year
Factory Workforce	Approximated 2000 persons
Warehouse Information	
Data Collected from	Multi-Product Warehouse
Items	Multiple Product
Warehouse space capacity	70000 Sq. ft.
Warehouse capacity	1 thousand furniture
Inventory system	Industrial Racking system and open floor
Staff	5
Workers	30

Table C6: Details of the raw data for the available KPIs of Brothers Furniture Ltd.

SL	KPI	Sep-19	Oct-19	Nov-19	Dec-19	Jan-20	Feb-20	Standard of KPIs		
								Max	Target	Min
1	Inventory Turnover Ratio	0.984	1.511	1.028	1.650	1.351	1.545	1.7	1.45	1.2
2	Inventory to Sales Ratio	0.437	0.247	0.387	0.563	0.450	0.618	0.75	0.55	0.35
3	Store Utilization (%)	66	73	79	76	84	70	90	75	60
4	Rate of Return (Ratio)	0.0077	0.0506	0.0624	0.0750	0.0450	0.0650	0.1	0.07	0.04
5	Orders per hour (Number)	1.09	0.89	1.37	2.31	1.75	1.56	2	1.5	1
6	Inventory Accuracy (%)	100	100	100	98	100	99	100	98	95
7	Damaged Inventory (%)	10	9	12	7	8	11	2	7	12
8	Perfect Order Rate	0.757	0.850	0.697	0.907	0.870	0.947	1	0.8	0.7
9	Order Lead Time (Days)	14	11	12	10	12	13	10	12	15
10	Downtime to Operating Time Ratio	0.081	0.087	0.061	0.067	0.086	0.076	0	0.1	0.2
11	On-time Delivery Percentage	44.78	50.17	81.77	67.45	79.87	75.32	100	70	40
12	Carrying Cost of Inventory ($)	50060	50766	55498	50600	52866	51448	50000	55000	60000
13	Labor Cost ($)	1175	1095	1287	1256	1015	1190	1000	1200	1500

Appendix D. Pairwise Comparison Matrix for the KPIs of Best Shirt Ltd.

See Table D1– Table D5.

Table D1: Pairwise comparison matrix for the four categories. (*CR Value = 0.098).

Item Description	Productivity	Quality	Time	cost
Productivity	1.00	0.33	3.00	3.00
Quality	3.03	1.00	2.00	3.00
Time	0.33	0.50	1.00	2.00
cost	0.33	0.33	0.50	1.00

Table D2: Pairwise comparison matrix for the KPI_1 to KPI_4. (*CR Value = 0.086).

Item Description	Inventory Turnover	Inventory to Sales Ratio	Store Utilization	Orders per hour
Inventory Turnover	1.00	7.00	5.00	3.00
Inventory to Sales Ratio	0.14	1.00	1.00	0.20
Store Utilization	0.20	1.00	1.00	1.00
Orders per hour	0.33	5.00	1.00	1.00

Table D3: Pairwise comparison matrix for the KPI_5 to KPI_7. (*CR Value = 0.0750).

Item Description	Inventory Accuracy	Stock-out Percentage	Perfect Order Rate
Inventory Accuracy	1.00	4.00	5.00
Stock-out Percentage	0.25	1.00	3.00
Perfect Order Rate	0.20	0.33	1.00

Table D4: Pairwise comparison matrix for the KPI_8 to KPI_{10}. (*CR Value = 0.057).

Item Description	Order Lead Time (Days)	Downtime to Operating Time Ratio	On-time Delivery Percentage
Order Lead Time (Days)	1.00	5.00	7.00
Downtime to Operating Time Ratio	0.20	1.00	3.00
On-time Delivery Percentage	0.14	0.33	1.00

Table D5: Pairwise comparison matrix for the KPI_{11} to KPI_{13}. (*CR Value = 0.070).

Item Description	Cost per Order ($)	Carrying Cost of Inventory ($)	Labor Cost ($)
Cost per Order ($)	1.00	7.00	1.00
Carrying Cost of Inventory ($)	0.14	1.00	0.33
Labor Cost ($)	1.00	3.00	1.00

Appendix E. Summary of Selected KPIs.

The sixteen distinct KPIs that have been selected from the literature and the opinion of experts for the three warehouses of three different industries in Bangladesh that are summarized in Table E1.

Table E1: The key summaries of the 16 KPIs for the three selected warehouses.

SL	Indicator	KPI Formula	Category
1	Inventory Turnover	$= \frac{Cost\ of\ Goods\ Sold}{Average\ Inventory}$	Productivity
2	Inventory to Sales Ratio	$= \frac{Inventory\ Value}{Sales\ Value}$	
3	Storage Utilization	$= \frac{Average\ Occupied\ Sq.Ft.}{Total\ Storage\ Capacity}$	
4	Rate of Return	$= \frac{Number\ of\ Units\ Returned}{Number\ of\ Units\ Sold}$	
5	Back Order Rate	$= \frac{Orders\ Unfilled\ at\ Time\ of\ Purchase}{Total\ Orders\ Placed}$	
6	Orders per Hour	$= \frac{Orders\ Picked/Packed}{Total\ Warehouse\ Labor\ Hours}$	
7	Inventory Accuracy	$= \frac{Database\ Inventory\ Count}{Physical\ Inventory\ Count}$	Quality
8	Damaged Inventory	$= \frac{Total\ Damage\ (Cost)}{Inventory\ Value\ (Cost)}$	
9	Stock-out percentage	$= \frac{Lost\ due\ to\ stockouts}{Total\ sales\ revenue} \times 100$	
10	Perfect Order Rate	$= \frac{Orders\ Completed\ Without\ Incident}{Total\ Orders\ Placed}$	
11	Order Lead Time	$= Time\ from\ order\ received\ to\ order\ delivered$	Time
12	Downtime to Operating Time Ratio	$= \frac{Total\ physical\ off\ time}{Total\ operating\ time}$	
13	On-Time Delivery percentage	$= \frac{Orders\ OnTime}{Total\ Orders\ Shipped} \times 100$	
14	Carrying Cost of Inventory	$= Inventory\ Carrying\ Rate \times Avg.Inventory\ Value$	Cost
15	Cost per order	$= \frac{Total\ Warehouse\ Cost}{Total\ Orders\ Shipped}$	
16	Labor Cost	$= Cost\ of\ personnel\ involved\ in\ warehouse\ management$	