Journal of Computational Design and Engineering, 2021, 8(2), 705–727

doi: 10.1093/jcde/qwab009
Journal homepage: www.jcde.org

RESEARCH ARTICLE

A novel particle swarm optimization-based grey model for the prediction of warehouse performance

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Abstract

Warehouses constitute a key component of supply chain networks. 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 preemptively estimate the overall warehouse performance (OWP), 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 a low forecasting error in order to precisely measure OWP. Incorporating advice from experts, conducting a literature review, and accepting the limitations of data availability, this study identifies 13 KPIs. The traditional grey method (GM)—the GM (1, 1) model—is established to estimate the grey data with limited historical information but not absolute. To reduce the limitations of GM (1, 1), this paper introduces a novel particle swarm optimization (PSO)-based grey model—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)—the discrete grey model—DGM (1, 1)—to assess the performance of the proposed model in terms of the mean absolute percentage error and other assessment metrics. The proposed model outperforms the existing grey models in projecting OWP through the forecasting of KPIs over a 5-month period. 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 quick OWP estimations in advance to take control measures regarding warehouse productivity and efficiency.

Keywords: Grey systems theory; PSO algorithm; PSOGM (1, 1) model; warehouse KPIs; OWP; Taguchi method

1. Introduction

Performance can be defined as the achievement of a given task measured against a predetermined standard (Rahman *et al.*, 2019). It is a critical element in operations management in various fields. Technically, it can be a helpful tool for measuring overall organizational efficiency and taking corrective action in advance. As such, there are various ways in which the managers are interested in measuring organizational performance. From a more recent perspective, an accurate prediction of the organizational performance is a crucial factor as studied by many researchers. While the measurement and prediction of supply chain performance are increasingly necessary—as warehousing is an essential component of logistics operations, contributing to the speed and profit of supply chains—they are also becoming

Received: 31 August 2020; **Revised:** 23 January 2021; **Accepted:** 30 January 2021

increasingly complex. The success of warehouse management depends largely on the measurement and estimation of the key performance indicators (KPIs; Krauth & Moonen, 2005). A KPI is a quantifiable metric that helps companies, experts, or workers assess their accomplishments 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 detail approaches to determining KPIs related to warehouse management (Krauth *et al.*, 2005; Johnson & McGinnis, 2011; Kusrini *et al.*, 2018). Today, managers are growing concerned over warehouse performance. At the same time, however, many KPIs have been developed to calculate warehouse efficiency. Of course, different warehouses require different methods and KPIs to evaluate their output. Thus, successfully managing warehouses and predicting their performance constitute a challenging issue that requires two crucial actions: the selection of the right KPIs and the accurate prediction of the KPI values based on historical data. The challenge of identifying KPIs for warehouses is mitigated by previous studies and experts' opinions on the subject. 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 nontraditional forecasting methodology focused on incomplete, ambiguous, scant, and fuzzy information. This theory, which was proposed by Deng (1982), is an excellent choice to define future trends for data from a time series with less prediction error.

Uncertain structures with small samples and insufficient knowledge are common in nature. This fact demonstrates the broad applicability of the theory of grey systems (Liu *et al.*, 2016). However, the traditional grey forecasting model, GM (1, 1), is not error free in predicting time-sequence data. Accuracy is a crucial matter in forecasting and, accordingly, researchers are devoted to achieving it. Since its conception, the traditional grey model has been enriched by many researchers; its prediction accuracy has been enhanced and various improved GM (1, 1) models have been established (Hsu & Chen, 2003; Madhi & Mohamed, 2016).

The optimization of a grey system is also an interesting research topic. The parameter optimization of the grey forecasting model can produce more accurate predictions than the traditional grey method. Various studies—including Cao *et al.* (2014), Lai *et al.* (2015), Hu and Jiang (2017), Li and Wang (2018), and Wang *et al.* (2009)—have sought to enhance the parameters of the traditional grey method and have concluded that their predicted outcomes are better than those of the GM (1, 1) model. In the ongoing pursuit of even greater accuracy, evolutionary algorithms constitute an alternative answer. To further the parameter optimization of the GM (1, 1) model, many researchers have arrived at the particle swarm optimization (PSO) algorithm (e.g. El-Shorbagy & Hassanien, 2018; Bansal, 2019). This study selects a basic PSO algorithm whose parameters are optimized through the Taguchi method to increase its search capability. This basic PSO employs the parameter optimization from various models with few dimensions (this study considers a 2D problem for the development parameters of the GM (1, 1) model; Shahnazar *et al.*, 2017; Zhang & Xia, 2017; Xu *et al.*, 2018; Lai *et al.*, 2019; Yang *et al.*, 2020).

Taken together, this study aims to develop a PSO-based grey forecasting model—PSOGM (1, 1)—to increase forecasting accuracy by controlling the parameters associated with the GM (1, 1) model. After selecting the right KPIs for the ready-made garment (RMG) warehouse in Bangladesh—which requires factors necessary for a developing country—the proposed grey model is implemented to predict the warehouse's KPI values and, in turn, predict its overall warehouse performance (OWP). Warehouse experts provided the weights for each KPI to accurately prioritize their effect on overall performance. This integrated model, as a methodological contribution to the warehousing industry domain, may help warehouse managers preemptively design, plan, and manage operations with great success. This study aims to answer the following research questions (RQs):

RQ 1: How can the PSO-based grey prediction model—PSOGM (1, 1)—be formed in a way that minimizes the prediction errors of time series data for single variables?

RQ 2: How can the developed model be used to calculate warehouse performance by predicting the values of warehouse KPIs?

By answering these questions, this study develops a framework to predict warehouse performance through a PSO-based grey prediction method. This proposed framework could improve warehouse performance and, in turn, enhance enterprises' supply chain efficiency.

This paper is organized as follows. Section 2 briefly describes relevant studies on the GM (1, 1) model, its improvements, and its applications. It addresses existing research gaps regarding its prediction accuracy and explains the contributions of this study to overcoming those gaps. Additionally, it details some previous studies on warehouse KPIs and performance models. Section 3 presents the theoretical background of this study. Section 4 elaborately explains the proposed methodology and discusses the parameter settings for the employed optimization algorithms. Section 5 demonstrates the application and details the results of the proposed methodology with a case study focused on the overall performance evaluation of an RMG warehouse. Finally, Section 6 discusses conclusions pertaining to the limitations of this study and the potential for further research in this field.

2. Literature Review

2.1. Grey prediction model—GM (1, 1)—and its improvement

The prediction method based on time series involves a moving average, 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. In the real world, there are countless indeterminate processes with limited samples and scant data; as such, the theory of gray systems is widely applicable in forecasting (Liu *et al.*, 2011; Cui *et al.*, 2013).

The GM (1, 1) forecasting model is one of the central models in the grey system theory commonly used in the analysis of time series data with less samples (Kayacan *et al.*, 2010). Grey forecasting is an umbrella term that includes sequence forecasting, calamity forecasting, 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 efficiently eliminates noise by transforming random time series data into a monotonically increasing sequence that 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 employed in the fields of climate (Dengiz *et al.*, 2019), energy (Li & Zhang, 2019; Lu, 2019), healthcare performance (Rahman *et al.*, 2019), industrial technology and safety (Lü & Lu, 2012), and petroleum exploration (Wang & Song, 2019), among others. Hui *et al.* (2009) used the GM (1, 1) model to forecast the growth of larches. Li *et al.* (2016) used it in an early warning system for predicting iron and steel incidents. The GM (1, 1) model has also been used to determine the number of fixture locations in sheet-metal operations (Yang *et al.*, 2017), to predict the likelihood of breast cancer (Iqelan, 2017), and to predict the research output of various countries (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 that combined residual adjustment and the ANN process. To enhance the predictive performance of the GM (1, 1) model, Tien (2009) modified it concerning the effect of the first entry of the original series. Cui *et al.* (2013) put forward a novel grey forecasting model alongside an optimized form called the NGM (1, 1) model.

Based on an error analysis of the GM (1, 1) model, Wang *et al.* (2009) proposed a new approach to optimizing background values in the model using the discrete function with nonhomogeneous exponential law to match the accumulated series. Lee and Tong (2011) proposed a GM (1, 1) model that combines a genetic algorithm (GA) with the GM (1, 1) model. Cao *et al.* (2014) and Ying *et al.* (2015) both developed a grey forecasting model with a background optimization technique that combined with the optimization of the initial item. To enhance the precision of the traditional GM (1, 1) model, Lai *et al.* (2015) proposed an upgraded grey prediction method using a back propagation neural network. Madhi and Mohamed (2016) paired background value optimization (BVO) 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 to predict electricity consumption using a moth-flame optimization (MFO) for its parameters. Seeking accurate power-load forecasting, Li and Wang (2018) proposed a traditional GM (1, 1) prediction model that incorporates BVO. Ding *et al.* (2018) proposed an updated GM (1, 1) model that incorporates initial condition optimization and rolling mechanism techniques. Hao *et al.* (2018) offered a GM (1, 1) model based on ANN and exponential smoothing to predict how many vehicles would ultimately be recycled.

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 that 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 aimed at specific targets (Fukuyama, 2007; Parsopoulos & Vrahatis, 2010; Olsson, 2011). Kennedy and Eberhart (1994) first developed the PSO algorithm after being inspired by natural populations, such as flocks of birds and schools of fish. The basic principles of the PSO process have been acquired from the following works. Zhang *et al.* (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. An extensive review of PSO's development and fundamental concepts can be found in El-Shorbagy and Hassanien (2018), Bansal (2019), and Wang *et al.* (2018).

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 processes (Bensingh *et al.*, 2019), indoor positioning systems (Guo *et al.*, 2019), algorithm performance improvement (Essiet *et al.*, 2018), and, in combination with ANN and a regression model, time series forecasting (Pradeepkumar & Ravi, 2017). However, there is still room for improvement in PSO performance. For example, due to the rapid convergence of PSO, it may drop into local optima in tackling multimodal optimization problems, potentially resulting in the early convergence of particle swarms. The location and speed of particles are randomly modified during simulations, leading to low computational efficiency. There are two key ways to enhance PSO efficiency: adjusting its parameters and combining it with other intelligent algorithms (Xu *et al.*, 2018; Ding *et al.*, 2019; Zhai *et al.*, 2020). To increase the robustness and the search performance of the PSO algorithm, this study utilizes the Taguchi method (Wang *et al.*, 2014; Chen *et al.*, 2016; Fathollahi-Fard *et al.*, 2018; Freddi & Salmon, 2019) to tune its parameters.

However, few studies in the literature have paired PSO with a grey prediction model for use in forecasting. Among these few studies, Zhou *et al.* (2009) applied PSO in the parameter optimization of the nonlinear grey Bernoulli model (NGBM); they optimized only the output coefficient of background value, p (mostly used as α), and Bernoulli differential equation parameter, r. Similar research was performed using the PSO-based grey model to predict traffic accidents (Qian *et al.*, 2011), electricity consumption (Ding *et al.*, 2018), and underground pressure (Ma *et al.*, 2011). Ma *et al.* (2013) optimized the output coefficient of background value α (here, λ) by incorporating the PSO algorithm into the conventional GM (1, 1) model. Wang *et al.* (2018) forecasted electricity consumption using a PSO-based grey GM (1, 1) model in which they used the optimization of the coefficient value and the production parameter, α (here, e).

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. They set the range of a as $[-0.5, 0.5]$ and the range of b as ($b \in [\min(a \times x^{(1)}(k-1) + x^{(0)}(k)),\ \max(a \times x^{(1)}(k) + x^{(0)}(k))]$, $k = 1, 2, \ldots, n$), which is actually dependent on the value of a. Xu *et al.* (2017) proposed a modified GM (1, 1) model that incorporated a PSO-optimized time response function (TRF). They used the traditional calculation method to determine the value of the development coefficients a and b. Meng *et al.* (2017) used PSO to optimize a and b in the grey model without defining the true range of those parameters. Similar research was performed to optimize a and b in the derived nonequigap grey Verhulst model (DNE grey Verhulst model; Wang & Li, 2019).

Ervural and Ervural (2018) 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 the range of b as $[b \in \min(0.5 \times x^{(0)}(k)), \max(0.5 \times x^{(0)}(k)), k = 1, 2, \ldots, n]$. However, the range of the coefficient b exceeds the limit when the randomness of a historical data series is higher. While many have used the PSO algorithm to optimize the development coefficients and background values in the grey model, few researchers have used the GA algorithm to do the same (Wang, 2013; Hu, 2017; Özcan & Tüysüz, 2018; Yahya *et al.*, 2020). The application of the improved grey model is summarized in Table 1.

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 abovementioned 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-squares method of the GM (1, 1) model using the range of the background value α [0, 1]. Therefore, the development of an improved, robust PSO-based grey model—the PSOGM (1, 1) model—is still required to accurately predict grey-type time series data and, in turn, yield the scope of this study.

2.2. Measuring warehouse performance

KPIs assess an enterprise's performance relative to its goals, thereby enabling corrective action when anomalies occur. The success of warehouse management largely depends on KPI measurement (Krauth & Moonen, 2005). It is an essential tool for operations management that connects execution, strategy, and overall value creation. Shifting market patterns put intense demands on conventional metric systems and cause tension between firms and supply chains. Melnyk *et al.* (2004) conveyed the value and significance of research related to function metrics, the dissimilarity between metrics, and metrics systems.

There are many KPIs identified in the literature that pertain to warehouse management. Krauth and Moonen (2005) identified about 130 warehouse metrics, classifying them as either short-term or long-term performance indicators. They then split the metrics further into five categories: effectiveness, efficiency, satisfaction, IT, and innovation. Krauth *et al.* (2005) published a literature review of several fields related to performance measurement, including logistics, supply chain management, service provision, and warehouse management. Johnson and McGinnis (2011) looked at the evaluation methods for the functional performance of warehouses, applying a new methodology to a large sample of warehouses.

Some studies (Staudt *et al.*, 2015a, b) 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 *et al.* (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, established KPIs for logistics companies, and identified critical warehouse-management functions and processes. They suggested eight KPIs concentrated on efficiency, accuracy, cost, security, and timeliness. 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 to evaluate the final score regarding the benchmark data on warehouse performance. Wudhikarn *et al.* (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 warehouse in 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, 13 KPIs are selected and placed under one of the four main categories—these are shown in Table 2. The KPIs' definitions and equations are taken from Manrodt *et al.* (2015), Eubank (2018), Richardson (2018), Sunol (2019), and Weiss (2018). 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), KPI ranking (Shahin & Mahbod, 2007; Bhatti & Awan, 2014; Kaganski *et al.*, 2018), and supply chains (Anjomshoae *et al.*, 2019).

3. Theoretical Background

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 functions through the following steps:

Step 1. The original time series is given as $X^{(0)}$ for the n number of nonnegative samples (time point); this can be expressed as follows:

$$X^{(0)} = \left[x^{(0)}(1),\ x^{(0)}(2),\ \ldots,\ x^{(0)}(n)\right] \quad n \geq 4. \tag{1}$$

The actual data are transformed into monotonically increasing data sequences through the AGO, which attenuates the disorderliness and noise of the original series data. From the initial data sequences, the incremented data series $X^{(1)} = [x^{(1)}(1), x^{(1)}(2), \ldots, x^{(1)}(n)]$ can be obtained through the AGO as

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

Now, from the $X^{(1)}$ series, the mean-generated sequence $Z^{(1)} = [z^{(1)}(2), z^{(1)}(3), \ldots, z^{(1)}(n)]$ can be determined as

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

Here, α is called the adjustment element; its value is generally set as 0.5. However, the value of α can be in the range of [0, 1].

Step 2. The grey first-order differential equation can be established as follows:

$$x^{(0)}(k) + az^{(1)}(k) = b. \tag{4}$$

Table 1: Summary of the application of the improved GM (1, 1) model.

Authors	Contribution	Method	Error analysis	Case study
(Hsu & Chen, 2003)	• Design improved grey GM (1, 1) model, using residual modification with ANN	GM (1, 1)	MAPE	Power demand forecasting of Taiwan
	• Optimized parameter: background value, α	ANN		
(Tien, 2009)	• Develop new grey model, first entry grey model, FGM (1, 1)	GM (1, 1)	MAPE	Materials' tensile strength and failure time prediction
	• Optimized parameter: α	FGM (1, 1)		
(Zhou et al., 2009)	• NGBM is proposed combining GM (1, 1) with the Bernoulli differential equation	GM (1, 1)	MAPE	Power load forecasting of Hubei (sample 1996–2007)
	• Optimized parameter: α	PSO		
(Wang et al., 2009)	• Improved GM (1, 1) model through nonhomogeneous exponential law to fit the accumulated sequence of the grey model	GM (1, 1)	MAPE	Financial investment in S&T (1998–2002: simulation and 2002–2004: prediction)
	• Optimized parameter: α	Integral formula		
(Lee & Tong, 2011)	• Design improved GM (1, 1) model, using GA	GM (1, 1)	MAPE	Annual energy consumption of China (1990–2007)
	• Optimized parameter: α	GA		
(Ma et al., 2011)	• Underground pressure forecasting by developing improved GM (1, 1) model trough parameter optimization of the GM (1, 1) model	GM (1, 1)	MAPE	Data of UPWS of S5–6 working surface' first station of Changchun coal mine in China in June 2010
	• Optimized parameter: α	PSO	MAE (mean absolute deviation) TIC (Theil's inequality coefficients)	
(Qian et al., 2011)	• Developing improved PSO-based GM (1, 1) power model	GM (1, 1) power model, PSO	MAPE	Road traffic accidents in China during the period of 1990–2009
	• Optimized parameter: background value, α, and c, a parameter of power mode			
(Ma et al., 2013)	• Introduce a high-precision hybrid model based on grey prediction and rolling mechanism optimized PSO	GM (1, 1),	MAPE	China' iron ore import and consumption, Statistical Yearbook (1996–2011)
	• Optimized parameter: α (here termed as λ)	PSO,		
		Rolling GM (1, 1)		
(Cao et al., 2014)	• Optimizing the background value and initial item	GM (1, 1)	MAPE	Numerical data sequence (source unknown)
	• Optimized parameter: α and initial value of the TRF	Integral formula		
(Lai et al., 2015)	• Design an improved grey model based on ANN to better predict market demand after transportation disruption	GM (1, 1)	MAPE	Weekly effective sales between January and March in HX factory
	• Divide the original data sequence into $n - 3$ subsequences and choose the best series for future prediction	ANN		
(Ying et al., 2015)	• Develop an optimized grey model	GM (1, 1)	MAPE	Prediction of bearing sleeve wear
	• Optimized parameter: α and initial value of the TRF	Function transformation		
(Madhi & Mohamed, 2016)	• Develop an optimized grey model	GM (1, 1)	MAPE	A sequence of $f(t) = 2e^{0.4t}$, $t = 1, 2, \ldots, 15$ is used
	• Optimized parameter: α	Integral formula		
(Zhao et al., 2016)	• Develop an optimized grey model with Rolling Mechanism	GM (1, 1)	MAPE	Electricity consumption (2001–2009) of Inner Mongolia

Table 1: Continued

Authors	Contribution	Method	Error analysis	Case study
(Li *et al.*, 2016)	• Optimized parameter: α • Develop an optimized grey model • Optimized parameter: development coefficients a and b depending on the initial setting of the raw data series	MFO GM (1, 1) PSO	MAPE MSE (mean square error) 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: α	GM (1, 1) ANN Residual model	MAPE	Annual electricity demand (1981–2002) of China, Statistical Yearbook (2014)
(Xu *et al.*, 2017)	• Introduce improved-response grey prediction model, IRGM (1, 1) • Optimized parameter: TRF parameters	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 but not specified the valid ranges of them	GM (1, 1) PSO	MAPE	Low rising and high rising data series (five 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 (mean absolute deviation), TIC	End-of-life vehicles recycled in Shanghai during 2005–2016
(Wang *et al.*, 2018)	• Develop a seasonal grey model (SGM (1, 1)) based on PSO • Optimized parameter: α	GM (1, 1) SGM (1, 1) PSO	MAPE RMSE (root mean square error) 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 coefficient, b	GM (1, 1) Interval grey number	Rationality analysis	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 but not specified the valid ranges of them	GM (1, 1) PSO GA	MAPE RMSE	Annual electricity consumption of Turkey (1996 and 2016)
(Wang & Li, 2019)	• Develop a grey Verhulst model based on PSO • Optimized parameter: development coefficients, a, and b but not specified the valid ranges of them	GM (1, 1) DNE-grey Verhulst, PSO	MAPE RMSE MAE	CO_2 emissions per capita from 1990 to 2014 in China

Table 2: The 13 KPIs for an RMG warehouse in Bangladesh.

Category	No.	Name	KPI formula
Productivity	1	Inventory turnover ratio	$= \frac{\text{Cost of Goods Sold}}{\text{Average Inventory}}$
	2	Inventory-to-sales ratio	$= \frac{\text{Inventory Value}}{\text{Sales Value}}$
	3	Storage utilization (ratio)	$= \frac{\text{Average Occupied Sq. Ft.}}{\text{Total Storage Capacity}}$
	4	Orders per hour (number)	$= \frac{\text{Orders Picked/Packed}}{\text{Total Warehouse Labor Hours}}$
Quality	5	Inventory accuracy (ratio)	$= \frac{\text{Database Inventory Count}}{\text{Physical Inventory Count}}$
	6	Stock-out percentage	$= \frac{\text{Lost due to stockouts}}{\text{Total sales revenue}} \times 100$
	7	Perfect order rate	$= \frac{\text{Orders Completed Without Incident}}{\text{Total Orders Placed}}$
Time	8	Order lead time (days)	= Time from order received to order delivered
	9	Downtime-to-operating time ratio	$= \frac{\text{Total physical off time}}{\text{Total operating time}}$
	10	On-time delivery percentage	$= \frac{\text{Orders OnTime}}{\text{Total Orders Shipped}} \times 100$
Cost	11	Cost per order ($)	$= \frac{\text{Total Warehouse Cost}}{\text{Total Orders Shipped}}$
	12	Carrying cost of inventory ($)	= Inventory Carrying Rate × Avg. Inventory Value
	13	Labor cost ($)	= Cost of personnel involved in warehouse management

Now, the image equation of equation (4) can be expressed as

$$\frac{dx^{(1)}}{dt} + a\,x^{(1)} = b. \tag{5}$$

The parameters a and b are the development coefficient and the control coefficient, respectively. These two parameters can be calculated using the approximation method of the linear regression:

$$\hat{a} = \begin{bmatrix} a \\ b \end{bmatrix} = \left[B^T B\right]^{-1} B^T\,Y, \tag{6}$$

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

Step 3. The grey forecasting formula can be constructed as

$$\hat{x}^{(1)}(k) = \left[x^{(0)}(1) - \frac{b}{a}\right] e^{-a(k-1)} + \frac{b}{a}. \tag{7}$$

The value of $\hat{x}^{(1)}(k)$ implies the forecast of $x^{(1)}(k)$ at time point k with the initial condition of $x^{(1)}(1) = x^{(0)}(1)$. The sequence of inverse AGO (IAGO) can be applied to calculate the forecasted value of $x^{(0)}(k)$ as $\hat{x}^{(1)}(k)$, as follows:

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

Step 4. The error associated with the simulation is analysed. There are many metrics available to measure the prediction error. Here, mean absolute percentage error (MAPE) is used to determine the forecasting error:

$$\text{MAPE} = \frac{1}{n}\sum_{k=1}^{n} \nabla_k \times 100, \tag{9}$$

where n is the total number of 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 kth raw data.

3.1.1. *Numerical example of the GM (1, 1) model*

To more clearly understand the working procedures of the GM (1, 1) forecasting model, this section presents a numerical example of progressively shifting time series data with a sample size of six (Liu *et al.*, 2016, p. 166).

Problem: $X^{(0)} = (60.7,\ 73.8,\ 86.2,\ 100.4,\ 123.3)$ is an original data sequence. Try to set a GM (1, 1) method with $X^{(0)}$ and measure the MAPE of prediction.

Solution: Here, $X^{(0)} = (60.7,\ 73.8,\ 86.2,\ 100.4,\ 123.3)$. From equation (6), we have

$$\hat{a} = \begin{bmatrix} a \\ b \end{bmatrix} = \left[B^T B\right]^{-1} B^T Y = \begin{bmatrix} -0.17241 \\ 55.889264 \end{bmatrix}.$$

Now, applying equation (7) and using the value of the coefficients a and b, the time response series can be formed as

$$\hat{x}^{(1)}(k) = \left[x^{(0)}(1) - \frac{b}{a}\right] e^{-a(k-1)} + \frac{b}{a}$$
$$= 384.865028\, e^{0.17241k} - 324.165028.$$

Then, the simulation series of $X^{(0)}$ obtained from equation (8) is as follows:

$$\hat{X}^{(0)} = \hat{x}^{(1)}(k) - \hat{x}^{(1)}(k-1)$$
$$= (60.7, 72.41804, 86.04456, 102.2351, 121.4721).$$

The corresponding error sequence is

$$\varepsilon = (0, 1.38196, 0.155434, -1.8351, 1.827829),$$
$$\text{where } \varepsilon(k) = x^{(0)}(k) - \hat{x}^{(0)}(k).$$

Therefore, using equation (9), the MAPE of this simulation is

$$\text{MAPE} = \frac{1}{5}\sum_{k=1}^{5} \nabla_k = 1.0726\%.$$

3.2. Discrete grey model (DGM) (1, 1) model

This study also considered the DGM (1, 1) model (Fei *et al.*, 2011; Yao *et al.*, 2012; Liu *et al.*, 2015; Dong *et al.*, 2017; Li *et al.*, 2018)—another basic form of the GM (1, 1) model—to compare its forecasting accuracy with that of the GM (1, 1) model. There is a slight difference between the two in their parameter calculations. The following equation is used in the DGM (1, 1) model as the difference equation rather than equation (4):

$$x^{(1)}(k+1) = \beta_1 x^{(1)}(k) + \beta_2, \tag{10}$$

where β_1 and β_2 are the coefficients of the proportion parameters. The vector parameter $\hat{\beta} = [\beta_1, \ \beta_1]^T$ in equation (10) is analogous to the formula of equation (6). There is also a slight difference in the matrices B and Y:

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

The time response formula can be written by equation (11), setting $x^{(1)}(1) = x^{(0)}(1)$ as

$$\hat{x}^{(1)}(k+1) = \beta_1^k \left(x^{(0)}(1) - \frac{\beta_2}{1-\beta_1} \right) + \frac{\beta_2}{1-\beta_1},$$
$$k = 1, 2, \ldots, n-1. \tag{11}$$

The restored value of $\hat{x}^{(1)}(k)$ is $\hat{x}^{(0)}(k)$, which can be determined by

$$\hat{x}^{(0)}(k+1) = \hat{x}^{(1)}(k+1) - \hat{x}^{(1)}(k), \ k = 1, 2, \ldots, n-1. \tag{12}$$

3.3. PSO

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

- **Velocity updating:**

$$v_{in}^{t+1} = wv_{in}^t + c_1 r_1 \left[p_{best,in}^t - x_{in}^t \right] + c_2 r_2 \left[g_{best,n}^t - x_{in}^t \right] \tag{13}$$

- **Position updating:**

$$x_{in}^{t+1} = x_{in}^t + v_{in}^{t+1} \tag{14}$$

- **Personal best update equation:** Considering the minimizing problem:

$$p_{best,in}^{t+1} = \begin{cases} p_{best,in}^t & if \ \ f_{in}^{t+1} > p_{best,in}^t \\ x_{in}^{t+1} & if \ \ f_{in}^{t+1} \leq p_{best,in}^t \end{cases} \tag{15}$$

- **Global best equation:**

$$g_{best} = arg\max \ or \ min \left\{ f\left(p_{best,i}^t \right) \right\} \tag{16}$$

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 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, update in the range of [0, 1] followed by a uniform distribution. w represents the inertia weight with a range of [0.1, 0.9].

- **Stopping:** Finally, a stopping criterion is needed to stop the algorithm.

3.4. GA

GA is a biologically inspired algorithm that aims to replicate the basic Darwinian principle of natural selection. The following five phases constitute a classic GA to generate the fittest candidates in every iteration (Kramer, 2017).

i. **Initial population**
The cycle starts with a group of individuals called a population. Each individual is a potential solution to the optimization problem, as each has a set of distinct modifications known as genes, which are combined to form a chromosome string (solution).

ii. **Fitness function**
The fitness function determines the ability of an individual to survive to the next iteration. It provides each individual with a fitness score. The likelihood of selecting an individual for reproduction depends on this score.

iii. **Selection**
In this phase, the most appropriate individuals are picked and allowed to transfer their genes to the next iteration or generation.

iv. **Crossover**
This phase 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 mates.

v. **Mutation**
Mutation operators are employed in the chromosome produced by the crossover operation. The frequency of this upheaval is known as the rate of mutation. Any of the genes may be subject to mutation with a low random probability in new offspring.

This algorithm is used in this study to develop the GA-based grey model (GAGM) (1, 1) model, in which the optimal values of the development coefficients a and b are determined through the GA.

4. Research Methodology

This study aims to improve the forecasted result of the GM (1, 1) model by proposing a tuned PSO-based grey prediction method—PSOGM (1, 1)—to predict the KPIs and estimate the overall performance of an RMG warehouse in Bangladesh. The research methodology adopted in this study is shown in Fig. 1.

The proposed methodology features four major phases:

a) Developing a PSO-based improved grey model—PSOGM (1, 1).
b) Tuning the parameters of the optimization algorithms.
c) Identifying KPIs for an RMG warehouse in Bangladesh.
d) Evaluating the overall performance of the warehouse.

The details of these four phases are covered by the following nine steps:

(i) A PSO-based grey model—PSOGM (1, 1)—is developed to optimize the basic grey model's development coefficients, a and b, which are directly related to the accuracy of the GM (1, 1) model.

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

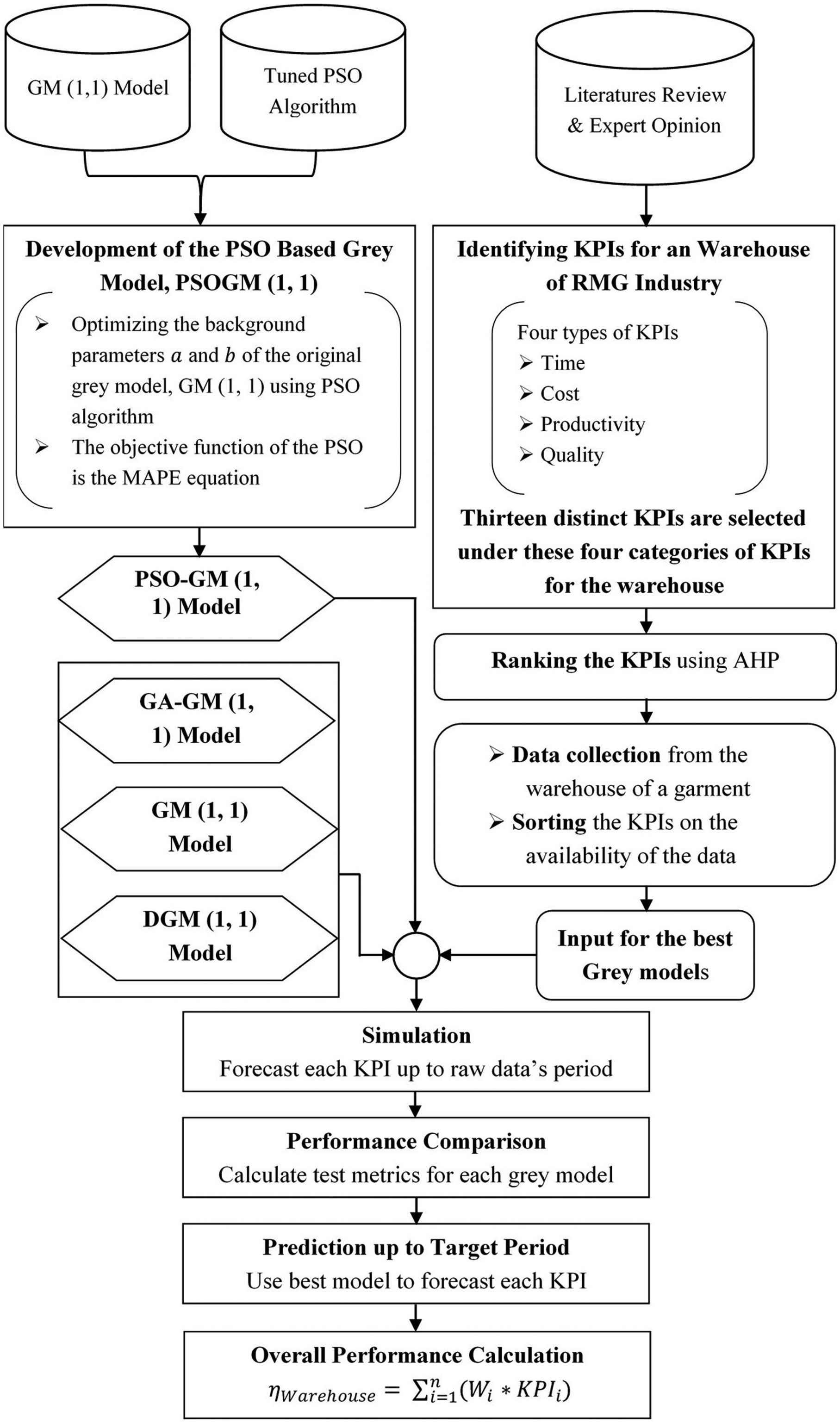

Figure 1: Proposed framework of the research.

(iii) To test the performance of the proposed model, the simulation result obtained from the PSOGM (1, 1) model—in terms of the MAPE value and three other metrics—is compared with that obtained from the GAGM (1, 1), GM (1, 1), and DGM (1, 1) models.

(iv) To increase the performance of the optimization algorithms, the PSO algorithm and the GA are tuned through the Taguchi method for better search results using the MAPE as a test function for known time series data.

(v) A case study is performed to predict the overall performance of an RMG warehouse in Bangladesh using the selected KPIs; this is done to evaluate the performance of the proposed model in a real-life problem.
(vi) A Bangladeshi company's warehouse is deliberately selected to collect data for the KPIs; these are then prioritized using the AHP.
(vii) The KPIs are used as inputs in the selected grey model simulations; the best model is used to predict the future KPI values through the target period.
(viii) The predicted KPI values are used to forecast the overall efficiency of the warehouse through a weighted sum formula.
(ix) The simulation and statistical analysis are carried out for both the traditional and proposed models using the MATLAB software. The Microsoft Excel tool is also used for the AHP method to prioritize the selected KPIs.

4.1. PSO-based grey model

Input for the model:

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

$$X^{(0)} = \left[x^{(0)}(1),\ x^{(0)}(2),\ \ldots,\ x^{(0)}(n)\right],\ n \geq 4. \tag{17}$$

(b) Input for the parameters and the objective function of the PSO algorithm (here, the MAPE function is used), and (c) logical ranges of the development coefficient, a, and the control coefficient, b; these are set by mean sequence generation of the GM (1, 1) model for the three values of the positioned coefficient—α as $\alpha = 0.0$; $\alpha = 0.5$; and $\alpha = 1.0$.

$$Z^{(1)}(k) = \alpha x^{(1)}(k) + (1-\alpha)\, x^{(1)}(k-1),\ k = 2, 3, \ldots\ldots, n \tag{18}$$

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

$$\hat{a} = \begin{bmatrix} a \\ b \end{bmatrix} = \left[B^T B\right]^{-1} B^T\, Y. \tag{19}$$

The maximum and minimum values are selected from the calculated values for the coefficients a and b to set the boundaries of those parameters.

Building the model:

Step 1. Consider a swarm of particles with locations $[x_i = x_{i1},\ x_{i2},\ \ldots,\ x_{iN}]$ and velocities $[v_i = v_{i1},\ v_{i2},\ \ldots,\ v_{iN}]$ 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 S denotes swarm size.

Step 2. All particles' fitness values are evaluated as

$$f(x) = \text{MAPE} = \frac{1}{n}\sum_{k=1}^{n} \frac{\left|x^{(0)}(k) - f^{(0)}(k)\right|}{x^{(0)}(k)}\ k = 1, 2, \ldots\ldots, n, \tag{20}$$

where n indicates the sample size, $x^{(0)}(k)$ indicates raw data, and $f^{(0)}(k)$ indicates the predicted value of the raw data. The predicted value, $f^{(0)}(k)$, is determined as follows:

$$f^{(1)}(k) = \left[x^{(0)}(1) - \frac{b}{a}\right] e^{-a(k-1)} + \frac{b}{a} \tag{21}$$

$$f^{(0)}(k) = f^{(1)}(k) - f^{(1)}(k-1),\ k = 2, 3, \ldots, n, \tag{22}$$

where $f^{(1)}(k)$ and $f^{(0)}(k)$ constitute the forecasts of $x^{(1)}(k)$ and $x^{(0)}(1)$, respectively, at time point k with the initial condition of $x^{(1)}(1) = x^{(0)}(1)$.

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

$$v_{in}^{t+1} = Wv_{in}^{t} + c_1 r_1^t\left[p_{best,in}^{t} - x_{in}^{t}\right] + c_2 r_2^t\left[g_{best,n}^{t} - x_{in}^{t}\right] \tag{23}$$

$$x_{in}^{t+1} = x_{in}^{t} + v_{in}^{t+1}, \tag{24}$$

where the cognitive coefficient c_1 and social acceleration coefficient c_2 are constants in [0, 2], the random variables r_1^t and r_2^t are taken in each iteration randomly in the range of [0, 1], and W indicates inertia weight, which can be updated at every iteration in line with a formula in the range of [0, 1].

Step 4. Each particle's personal best, $p_{best,\ in}^{t+1}$, for the minimizing problem is determined as

$$p_{best,in}^{t+1} = \begin{cases} p_{best,in}^{t} & if\ \ f_{in}^{t+1} > p_{best,in}^{t} \\ x_{in}^{t+1} & if\ \ f_{in}^{t+1} \leq p_{best,in}^{t} \end{cases}. \tag{25}$$

Step 5. The global best, $g_{best,\ n}^{t}$, is evaluated as

$$g_{best,n}^{t} = arg\max \text{ or } min\ \left\{f\left(p_{best,i}^{t}\right)\right\}. \tag{26}$$

Step 6. The iteration number is updated by $t = t + 1$. The process then returns to '**Step 1**'; the cycle is repeated until the iteration number exceeds t_{max}. After completing this process, a particle with the best functional value is found; 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, which were obtained from the above steps, are used in the grey time series forecasting equation:

$$f^{(1)}(k) = \left[x^{(0)}(1) - \frac{b^{opt}}{a^{opt}}\right] e^{-a^{opt}(k-1)} + \frac{b^{opt}}{a^{opt}}. \tag{27}$$

The final forecasted value of the original raw data is obtained through the IAGO operation in equation (22). The pseudo-code of the PSOGM (1, 1) method is illustrated in Fig. 2 based on the procedures of the proposed model detailed above.

4.2. 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:

$$S/N = -10 \times \log_{10}^{(\text{MAPE})^2}, \tag{28}$$

where the equation of MAPE is used as the objective function for PSO and GA. Table 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.

For the "Strategy of Inertia Weight (W)" in the above table, four strategies are selected from fifteen possible strategies for

START
Input the historical data series
Set PSO Parameters
Set the boundary for the grey coefficients a and b
Initialize population
REPEAT
a. Evaluate the attribute fitness based on MAPE value
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, p_{best}
d. Keep comparing Fitness Analysis to the overall p_{best}
e. Among all the p_{best} the best value is the Global Best, g_{best}
f. Velocity and location upgraded and generate a new population
g. Increment t as t= t +1
UNTIL the population has converged or maximum iteration, t_{max}
h. The optimized values, a^{opt} and 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

Figure 2: Pseudo-code of the PSOGM (1, 1) method.

Table 3: 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

Table 4: The L16 orthogonal array for the PSO.

Run	Maximum iteration (Maxit)	Population size (Npop)	Acceleration coefficient (C1)	Acceleration coefficient (C2)	Strategy of inertia weight (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

the PSO algorithm discussed by Bansal *et al.* (2011). The numbers 1–4 in the table indicate the following inertia strategy consequently.

Strategy 1: A constant value is set for W, as W = 0.7.

Strategy 2: Linearly decreased inertia weight is generated by

$$W = W_{max} - \left(\frac{(W_{max} - W_{min})}{t_{max}} \right) \times t. \tag{29}$$

Table 5: The L16 orthogonal array for the GA.

Run	Number of population (Npop)	Crossover probability (CP)	Uniform mutation rate (MR)	Number of generations (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	0.10	500
5	30	0.4	0.03	200
6	30	0.6	0.01	500
7	30	0.8	0.10	50
8	30	0.9	0.05	100
9	50	0.4	0.05	500
10	50	0.6	0.10	200
11	50	0.8	0.01	100
12	50	0.9	0.03	50
13	100	0.4	0.10	100
14	100	0.6	0.05	50
15	100	0.8	0.03	500
16	100	0.9	0.01	200

Strategy 3: Here, W is randomly generated at each iteration by

$$W = 0.5 + \frac{rand\,()}{2}. \tag{30}$$

Strategy 4: Here, W is generated as

$$W = W_{min} + \left(\frac{W_{max} - W_{min}}{t_{max}}\right) \times \lambda^{(t-1)}. \tag{31}$$

In the above strategies, W_{max} and W_{min} express the highest and lowest values of the inertia weight, respectively, which are generally set as $W_{max} = 0.9$ and $W_{min} = 0.1$, and t_{max} denotes the maximum number of iterations. The value of 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). The average response value of MAPE obtained from both the PSOGM (1, 1) and GAGM (1, 1) models is used in the Taguchi analysis. The % of relative deviation (PRD; Fathollahi-Fard *et al.*, 2019, 2020) method is used to calculate the efficiency of algorithms. The PRD for minimizing problems is determined by the formula below:

$$PRD = \frac{Alg_{Response} - Min_{Response}}{Max_{Response} - Min_{Response}}, \tag{32}$$

where $Min_{Response}$ and $Max_{Response}$ represent the best and worse responses among all solutions, respectively, and $Alg_{Response}$ is the algorithm's solution. According to the number of levels and parameters in Table 3, the Taguchi process for PSO and GA has proposed the L16 orthogonal arrays shown in Tables 4 and 5, respectively. The higher a minimization optimization model's S/N value, the better the algorithm's efficiency. By comparison, the higher the optimizer's capability, the lower its PRD value.

The S/N ratio and mean PRD for each algorithm are shown in Figs 3–6. Analysing these figures and depending on the Taguchi analysis, the best level for each selected parameter in PSO and GA is displayed in Table 6.

4.3. Model evaluation metrics

Performance analysis is important in assessing the accuracy of forecasting models. To determine the effectiveness of each grey model, metrics are introduced to determine the result. In this study, the four most commonly used metrics are adopted to evaluate the efficiency of the forecasting models. These are MAPE, MAE, mean square percentage error (MSPE), and correlation coefficient (ξ), all of which are defined below (Wang & Song, 2019; Javed *et al.*, 2020; Wang *et al.*, 2020; Wu *et al.*, 2020; Xia *et al.*, 2020):

$$MAPE = \frac{1}{n} \times \sum_{k=1}^{n} \left| \frac{y^{(0)}(k) - f^{(0)}(k)}{y^{(0)}(k)} \right| \times 100 \tag{33}$$

$$MAE = \frac{1}{n} \times \sum_{k=1}^{n} \left| y^{(0)}(k) - f^{(0)}(k) \right| \tag{34}$$

$$MSPE = \frac{1}{n} \times \sqrt{\sum_{k=1}^{n} \left(\frac{y^{(0)}(k) - f^{(0)}(k)}{y^{(0)}(k)} \right)^2} \times 100 \tag{35}$$

$$\xi = \frac{1}{n} \times \sum_{k=1}^{n} \frac{min_i min_k \left|y^{(0)}(k) - f^{(0)}(k)\right| + \varphi\, max_i max_k \left|y^{(0)}(k) - f^{(0)}(k)\right|}{\left|y^{(0)}(k) - f^{(0)}(k)\right| + \varphi\, max_i max_k \left|y^{(0)}(k) - f^{(0)}(k)\right|}. \tag{36}$$

In these formulations, the upper three metrics require a value as close to 0 (zero) as possible; however, the lower metric requires a value as close to 1 (one) as possible. Additionally, $y^{(0)}(k)$ is the actual value, $f^{(0)}(k)$ is the forecasted value for $k = 1, 2, 3, \ldots\ldots, n$, and n is the number of data points. In equation (36), φ is the distinguishing coefficient; it is generally set as $\varphi = 0.5$. Among the four metrics, the MAPE is a popular goodness-of-fit indicator that has been utilized in numerous forecasting problems. Thus, in this study, MAPE is used as an objective function for the optimization algorithms. Following the Lewis scale (Javed *et al.*, 2020), which is shown below, an MAPE

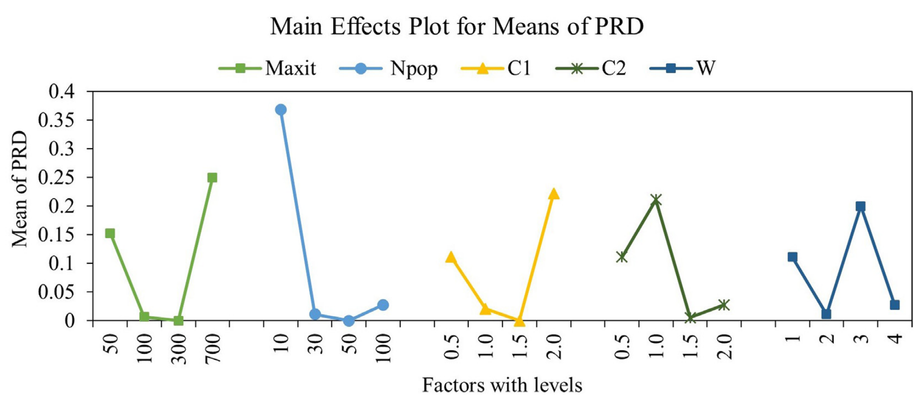

Figure 3: Main effects plot for means of PRD for PSO's parameters.

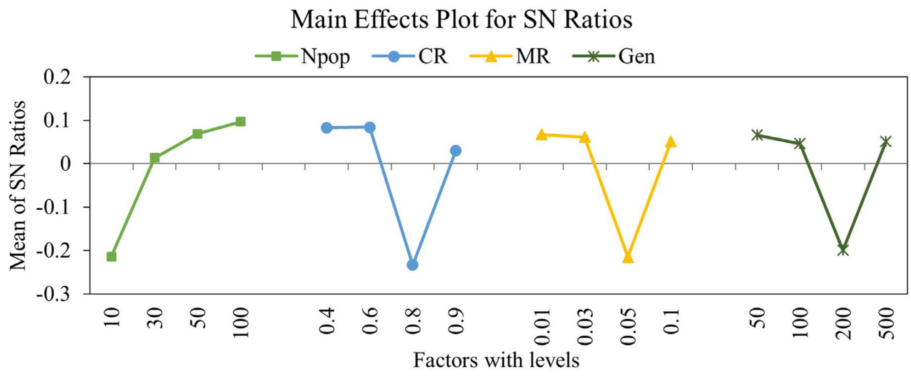

Figure 6: Main effects plot for S/N ratios for GA's parameters.

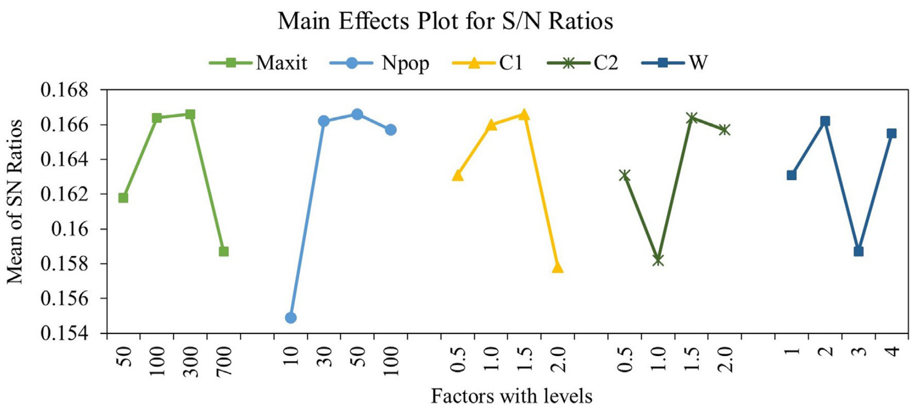

Figure 4: Main effects plot for S/N ratios for PSO's parameters.

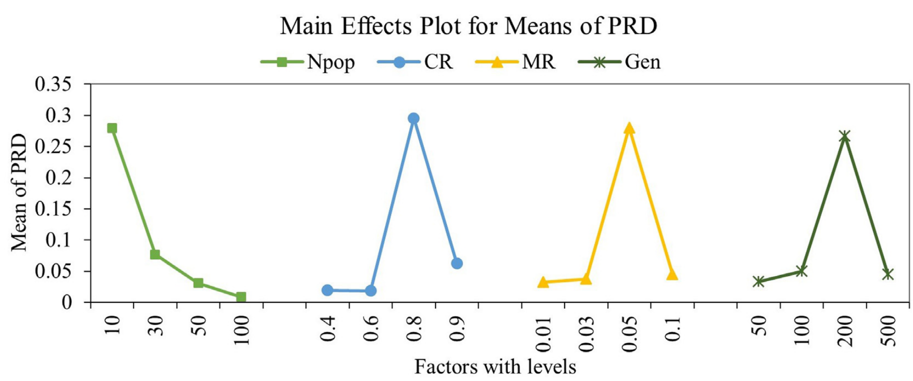

Figure 5: Main effects plot for means of PRD for GA's parameters.

of less than 20% is indicative of a good forecast.

$$\text{MAPE }(\%) = \begin{cases} < 10 & \text{Highly accurate forecast} \\ 10\text{–}20 & \text{Good forecast} \\ 20\text{–}50 & \text{Reasonable forecast} \\ > 50 & \text{Inaccurate forecast} \end{cases}$$

5. Practical Implementation of the Proposed Model

This section details the application of the proposed grey model to a real-world problem. In this case study, we evaluate OWP prediction through the forecasting of KPIs for an RMG warehouse in Bangladesh. This evaluation helps industrial managers make improvements in advance, root out problems' causes, and develop sustainable planning measures.

5.1. Data collection

The KPI data are being collected from a warehouse owned by Best Shirts Ltd in Dhaka, Bangladesh. This is a Bangladeshi RMG company that sells most of its products abroad. Generally, it is a single-product warehouse. It boasts of a very low variety of items; it mainly stores fabrics as its main item. The information

Table 6: 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

used in this study was provided by a senior executive (Industrial Engineering), a planning officer, and three other officers at the company. Table 7 displays the raw KPI data.

The standard values in Table 7 indicate the target point set by the authority. The most recent data are unavailable due to the COVID-19 pandemic, during which production has been disrupted.

5.2. Simulation and prediction of KPIs

The simulation and prediction of each KPI are performed using MATLAB R2017a. Figure 7 depicts the simulation and computational time for 13 KPIs obtained from the grey models. This figure indicates that the forecasted line of the proposed model fits well with the actual data. However, the second data point of the KPI-11 deviates to a greater degree than the other three models. Importantly though, the overall analysis of the figure suggests that the PSOGM (1, 1) model performs better than the other models. The forecasting accuracy of the four models is displayed in Table 8.

In the chart N of the above figure, the computational times of the GM (1, 1) and DGM (1, 1) models are almost identical and lower than the computational times of the PSOGM (1, 1) and GAGM (1, 1) models. The latter two had higher computational times due to the integration of the optimization algorithm in the GM (1, 1) model. It is important to note that the computational time of the PSOGM (1, 1) model is significantly less than that of the GAGM (1, 1) model, which proves the dominance of the proposed model.

According to Table 8, the proposed model boasts a more accurate forecast than the other three grey models across all 13 KPIs in terms of MAPE, MAE, and ζ. In terms of MSPE, the proposed model shows a minor degree of deviation from the other models for a few KPIs. Among the other three models, the GAGM (1, 1) model performs best. Table 8 also indicates that the performance of the two basic grey models, GM (1, 1) and DGM (1, 1), is almost identical across all KPIs. Furthermore, it suggests that the values of certain metrics do not significantly vary for a few KPIs (KPI 4, KPI 5, and KPI 13). 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 5 months from the end period of the actual data, which is shown in Table 9.

5.3. Weight calculation for each KPI

Since the importance of each KPI is unequal, their effect on the OWP will also be unequal. To determine the global weight of each KPI, this study employs the AHP method; the final KPI scores are shown in Table 10. 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 (Table A1, Table A2, Table A3, Table A4, Table A5).

According to Table 10, 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.

Table 7: KPI data for the selected RMG 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	Inventor-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
4	Orders per hour	223.45	172.50	198.62	206.90	189.09	188.50	185
5	Inventory accuracy (0–1 scale)	0.91	1.00	1.00	0.92	1.00	0.98	1
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	0.1
10	On-time delivery percentage	96	99	97	100	95	98	100
11	Cost per order ($)	173.71	317.43	145.25	183.00	168.00	195.00	250
12	Carrying cost of inventory ($)	6150	6500	6000	6400	5600	6720	6000
13	Labor cost ($)	10100	9375	10688	9125	9750	10875	10000

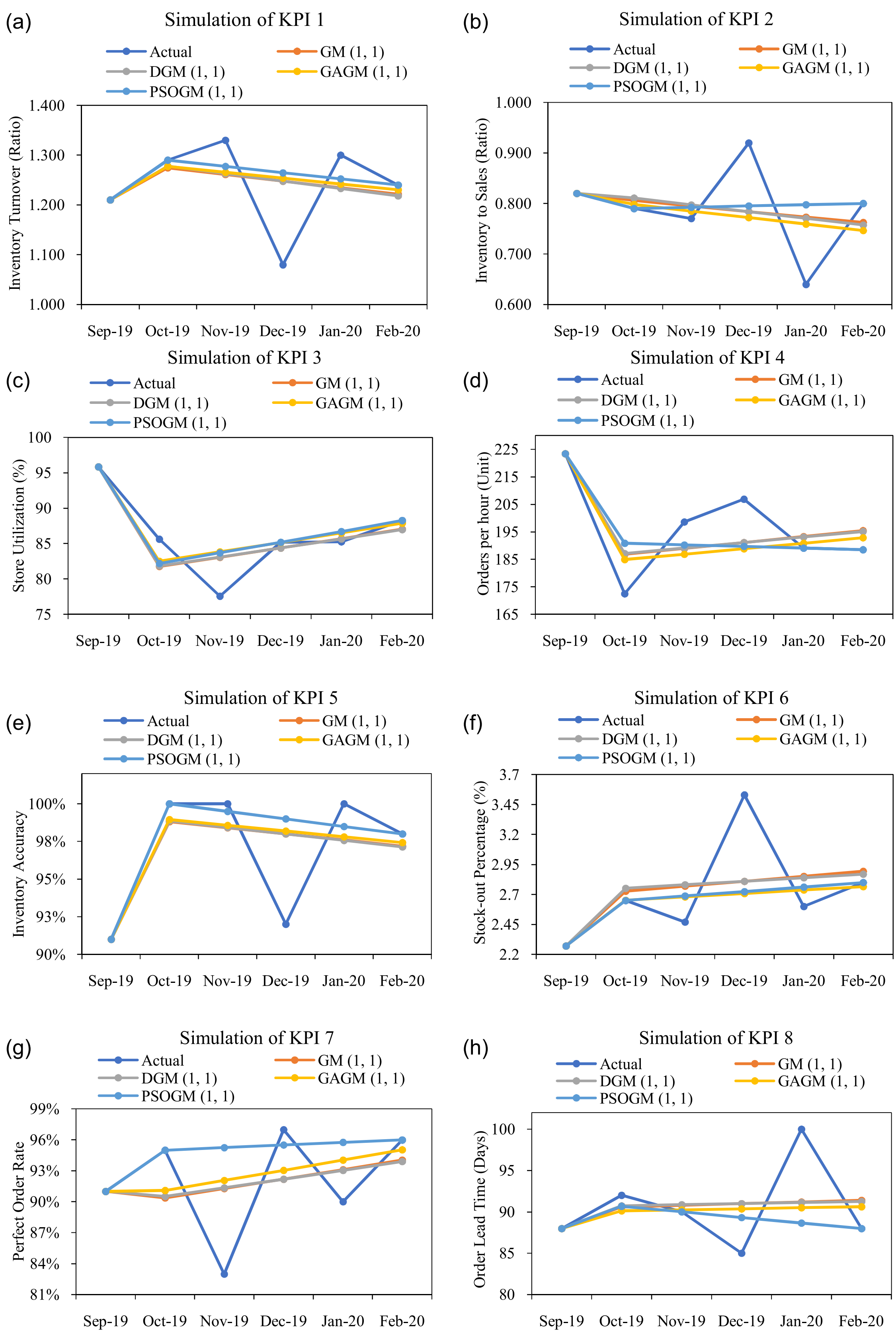

Figure 7: Illustration of the simulation [A-M] and computational time [N] for 13 KPIs of the 4 grey models.

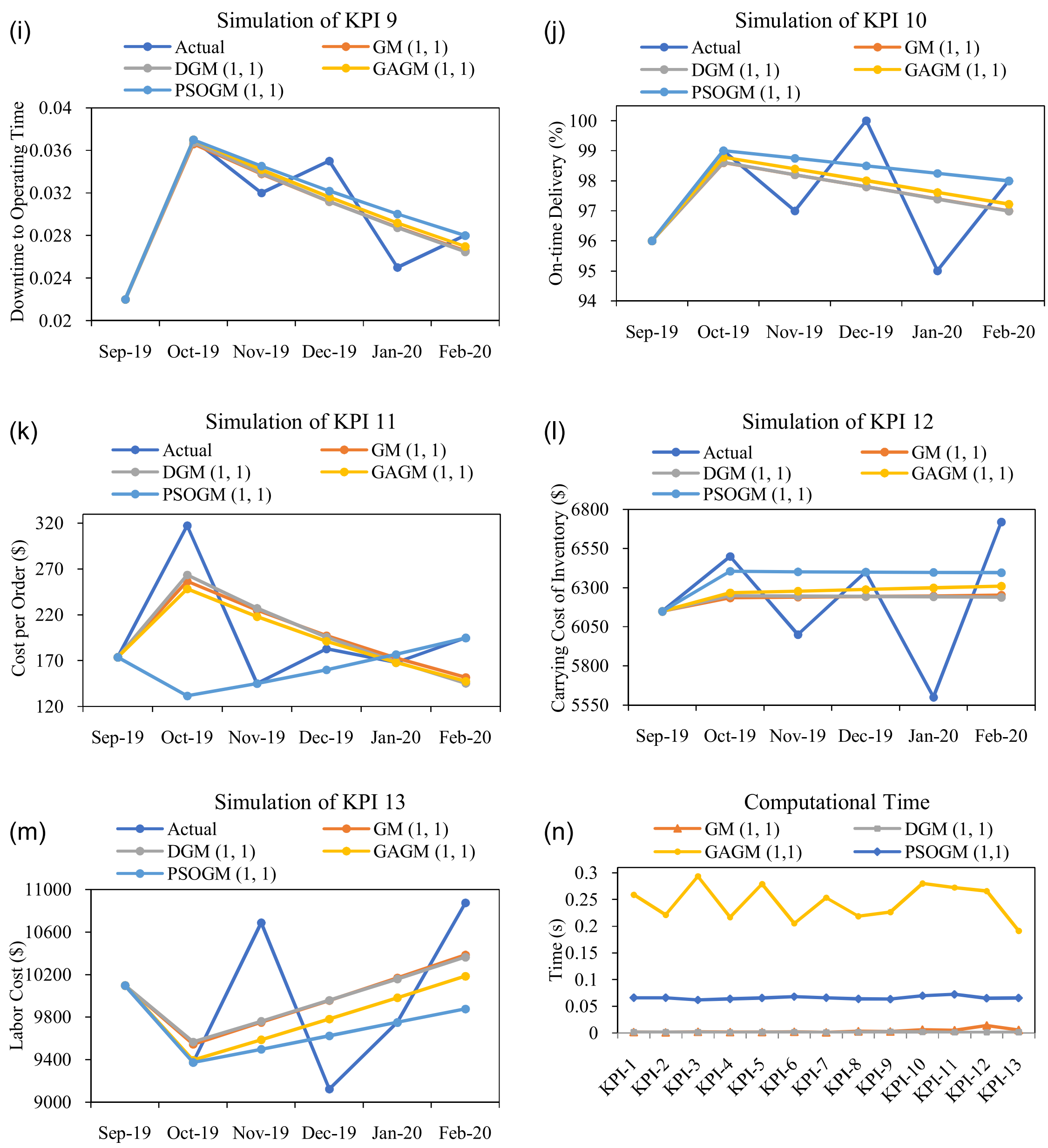

Figure 7: Continued.

5.4. OWP prediction

The OWP of the selected RMG warehouse, represented as $\eta_{\text{Warehouse}}$, is measured by the following equation:

$$\eta_{\text{Warehouse}} = \sum_{i=1}^{n} (W_i \times \text{KPI}_i), \tag{37}$$

where W_i indicates the global weights of each KPI, which are obtained from Table 10. The KPI values are not directly applicable to performance measurement. Before calculating overall performance, the forecasted KPI values must be converted to normalized values. This normalization is done in the range of [0.7, 1.0] using the following equation:

$$\text{Normalization} = l + \frac{(X - L)(u - l)}{(U - L)}, \tag{38}$$

where l is the minimum value of the desired range (0.7) and u is the maximum value of the desired range (1.0). X indicates the values that must be normalized. L and U are the minimum and maximum values of the data that must be normalized, respectively. Finally, applying equations (37) and (38), OWP is measured using the normalized KPI values, which are presented in Table 11. A graphical illustration is shown in Fig. 8; this illustrates the dominant trend by utilizing the measured overall performance.

The final result constitutes a small deviation from the preset standard of 90%. This deviation entirely depends on KPI data and the global weights obtained through the AHP process.

Table 8: Accuracy comparison of the four grey models.

KPIs	Performance matric	Model			
		GM (1, 1)	DGM (1, 1)	GAGM (1, 1)	PSOGM (1, 1)
KPI 1	MAPE	4.74%	4.74%	4.52%	4.12%
	MAE	0.0560	0.0560	0.0530	0.0475
	MSPE	2.87%	2.87%	2.90%	2.89%
	ζ	0.6851	0.6855	0.7141	0.7716
KPI 2	MAPE	7.59%	7.78%	7.40%	6.85%
	MAE	0.0579	0.0595	0.0573	0.0508
	MSPE	4.37%	4.36%	4.26%	4.41%
	ζ	0.6432	0.6290	0.6715	0.7496
KPI 3	MAPE	2.41%	2.41%	2.28%	2.27%
	MAE	1.9762	1.9761	1.8440	1.8349
	MSPE	1.43%	1.43%	1.50%	1.50%
	ζ	0.6786	0.6797	0.7377	0.7473
KPI 4	MAPE	4.45%	4.43%	4.18%	3.86%
	MAE	8.4894	8.4369	8.0560	7.3223
	MSPE	2.17%	2.17%	2.17%	2.18%
	ζ	0.5541	0.5571	0.6166	0.7009
KPI 5	MAPE	2.09%	2.09%	2.00%	1.60%
	MAE	0.02	0.0200	0.0191	0.015
	MSPE	1.26%	1.26%	1.26%	1.26%
	ζ	0.6741	0.6740	0.6983	0.8178
KPI 6	MAPE	8.07%	8.09%	6.38%	6.30%
	MAE	0.2402	0.2403	0.2006	0.1974
	MSPE	4.54%	4.55%	4.36%	4.34%
	ζ	0.6810	0.6814	0.7777	0.7829
KPI 7	MAPE	4.22%	4.22%	4.10%	3.78%
	MAE	0.0380	0.0380	0.0365	0.0325
	MSPE	2.13%	2.14%	2.20%	2.23%
	ζ	0.5863	0.5874	0.6264	0.7754
KPI 8	MAPE	3.69%	3.66%	3.52%	2.98%
	MAE	3.3999	3.3766	3.2706	2.8317
	MSPE	2.01%	2.01%	2.00%	2.01%
	ζ	0.6542	0.6583	0.6857	0.7852
KPI 9	MAPE	6.30%	6.30%	6.17%	5.99%
	MAE	0.0019	0.0019	0.0018	0.0017
	MSPE	3.36%	3.35%	3.48%	3.43%
	ζ	0.5975	0.6021	0.6454	0.7175
KPI 10	MAPE	1.23%	1.23%	1.20%	1.12%
	MAE	1.1995	1.1994	1.1652	1.0832
	MSPE	0.62%	0.62%	0.63%	0.64%
	ζ	0.5804	0.5803	0.6170	0.7224
KPI 11	MAPE	17.85%	17.71%	16.80%	12.70%
	MAE	33.8729	33.1638	32.9651	36.2155
	MSPE	10.47%	10.75%	10.00%	10.01%
	ζ	0.6387	0.6598	0.6539	0.8417
KPI 12	MAPE	4.84%	4.84%	4.76%	4.54%
	MAE	295.999	296.001	288.652	270
	MSPE	2.48%	2.47%	2.53%	2.76%
	ζ	0.5905	0.5888	0.6179	0.6982
KPI 13	MAPE	4.76%	4.79%	4.41%	4.29%
	MAE	475.112	478.789	450.173	447.448
	MSPE	2.37%	2.37%	2.38%	2.37%
	ζ	0.5739	0.5672	0.6497	0.7085

One partial cause that may be responsible for the small deviation is the fact that the randomness of the raw data is very low.

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.

6. Conclusions

This study contributed to the improvement of the GM (1, 1) model's prediction accuracy by incorporating the PSO algorithm to minimize the grey model's development coefficients. The proposed model, named PSOGM (1, 1), was used to predict the overall performance of an RMG warehouse in Bangladesh through the forecasting of its KPIs. The performance of the PSOGM (1, 1) model was compared to that of three other grey models—the GAGM (1, 1), DGM (1, 1), and GM (1, 1) models. The evaluation index MAPE was used to validate the performances of the integrated models. The primary outcomes of this study can be summarized as follows:

I. Defined a new way to optimize the development coefficients' ranges using the optimization algorithm, which directly solves the limitation found in the literature (Ervural & Ervural, 2018) through which highly variable data cannot satisfy the range set for the coefficient *b*.
II. Designed robust parameters for PSO and GA using the Taguchi process to increase the search efficiency of the hybrid grey model; this was done based on the MAPE as a minimizing objective function.
III. Identified 13 KPIs for an RMG warehouse in Bangladesh. These were ranked using the AHP method according to the specific warehouse. OWP of the warehouse was measured by forecasting the values of each KPI using the proposed model.
IV. The proposed model showed promising results relative to the other grey models in terms of the four accuracy-testing metrics. It reduces the MAPE by 6–29% for the selected KPIs; this reduction is more significant than that stemming from the GM (1, 1), GAGM (1, 1), or DGM (1, 1) model. This performance index revealed that the PSOGM (1, 1) model outperformed the other grey models.

These findings and the proposed model can help warehouse professionals make quick estimations of warehouse KPIs. This can help them measure OWP ahead of time and, in turn, avoid massive losses. Additionally, this study can provide mathematical support in the design of warehouse performance dashboards and smart manufacturing systems by integrating the Internet of things into the warehousing system. This study only considered MAPE criteria as constituting the objective function for the PSO and GA. However, for future work, there are

Table 9: Prediction of each KPI for the selected warehouse over the next 5 months.

SL	KPIs	Forecasted values				
		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	91.46	93.10	94.77	96.47
4	Orders per hour	187.91	187.33	186.74	186.16	185.58
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 ($)	10 008.30	10 140.00	10 273.44	10 408.63	10 545.60

Table 10: Local and global weights of each KPI.

Category	Local weight of category	KPI	Symbol	Local weight of each KPI	Global weight, W_i[a]
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%

[a] *W_i = Local weight of category × local weight of each KPI.*

Table 11: Performance prediction through normalized forecasted KPI values.

Indicators	Symbol	Global weight, W_i	Normalized forecasted KPIs value				
			Mar-20	Apr-20	May-20	June-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, $\eta_{\text{Warehouse}}$ =			90.55%	89.79%	89.00%	88.19%	87.38%

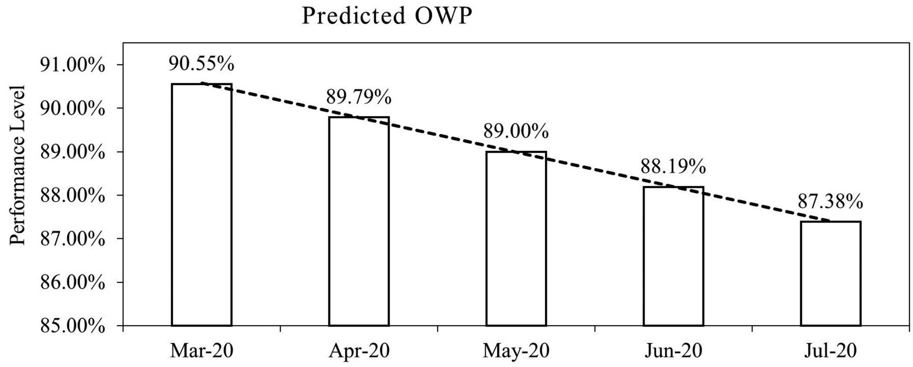

Figure 8: Forecasted overall performance of the Best Shirt Ltd warehouse.

more methods that can be used to analyse forecasting error, which may all be considered together as multiple objective functions for the optimization algorithms, i.e. multiobjective optimization. A Big O notation analysis could also be performed by future studies to get a more accurate result than the current method.

Acknowledgement

This research work was carried out at Bangladesh University of Engineering and Technology (BUET), Dhaka, Bangladesh. The authors acknowledge the supports received from the Department of Industrial and Production Engineering of BUET to carry out the research work successfully. The last author acknowledges the financial support through Natural Science Engineering Research Council Canada Discovery Grant Program (RGPIN-2019-04704) for professional editing and proofreading.

Conflict of interest statement

None declared.

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Appendix: Pairwise Comparison Matrices for Five Experts

Table A1: Pairwise comparison matrix for the four categories.

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

*CR value = 0.098.

Table A2: Pairwise comparison matrix for KPI-1 to KPI-4 under the category of Productivity.

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

*CR value = 0.086.

Table A3: Pairwise comparison matrix for KPI-5 to KPI-7 under the category of Quality.

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

*CR value = 0.0750.

Table A4: Pairwise comparison matrix for KPI-8 to KPI-10 under the category of Time.

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

*CR value = 0.057.

Table A5: Pairwise comparison matrix for KPI-11 to KPI-13 under the category of Cost.

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

*CR value = 0.070.