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Research Article

A Study on Disabling Injuries Prediction of Taiwan Occupational Disaster with Grey Rolling Model

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In order to protect the safety and health of laborers and to achieve the goal of zero occupational accidents at work, the study takes the top three industries with the highest number of laborers inspections from 2010 to 2019, namely, construction, manufacturing, wholesale, and retail as the research object. Using three major indicators of disability injury including Disabling Frequency Rate, Disabling Severity Rate, and Frequency Severity Indicator as parameters, it applies grey theory to establish a GM (1,1) rolling forecast model. It further predicts the trend of disability injuries from 2020 to 2025. Based on the optimized GM (1,1) rolling model, the results show that there has the highest accuracy rate in the prediction of Disabling Frequency Rate (accuracy is 95.235% in K7) in construction. Disabling Severity Rate and Frequency Severity Indicator are both in wholesale and retail industries (accuracy is 97.044% in K6 and accuracy is 99.906% in K5). Therefore, Disabling Severity Rate has an upward trend, which is due to the common type of traffic accidents in the wholesale and retail industry. The study further proposes that relevant actual disaster cases could be the training materials and strengthen the communication in education to improve workers' safety awareness for occupational disaster prevention.

1. Introduction

1.1. Background. The causes of occupational disasters and safety management have always been the key issues of concern in various industries. Occupational disasters not only cause financial, human, and social capital losses to enterprises and the country but also have a great impact and harm on the laborers themselves. According to the reports on "Statistics of deaths and mortality rates in the top 10 dangerous jobs in the construction industry" from the Ministry of Labor of Taiwan, the type of disaster is mainly falling and occurs in small and medium-sized construction sites [1]. In addition, more than 70% of the affected workers have not taken relevant occupational safety training.

The Occupational Safety and Health Act [2] and the relevant provisions of the Occupational Safety and Health Education and Training Rules mentioned that enterprises should arrange workers to take training according to their job attributes. The types can be divided into 13 types, including special operators, supervisors of occupational safety and hazardous work, operators of dangerous machinery, and other safety and health education training. The cumulative average number of people in the past 10 years accounted for more than 80% [1]. That is, from 2010 to 2019, the number of people taking education and training has increased from 131,714 to 212,843 [1], which shows the implementation of safety training in enterprises. In addition to training, labor inspections are one of the effective prevention methods for occupational disasters [3]. Preinspection can be used to confirm safety deficiencies to reduce the probability of disasters [4]. In order to implement Labor Laws and Labor Inspection Laws, the top three industries with the highest average number of labor inspections were construction (51.34%), manufacturing (31.13%), wholesale, and retail (4.63%) from 2010 to 2019 [2].

1.2. Research Problem. Compared with other industries, the construction industry has more serious occupational disasters. In Taiwan, the frequency of disability from occupational disasters has shown a downward trend from 2.13 in 2006 to 1.39 in 2018 [2]. This not only serves as a benchmark for other countries to learn from, but it is also worthy of discussion and analysis of the reasons for the decline. At the same time, we also found that more than 70% of workers of the major occupational disasters in small- and medium-sized enterprises have not received relevant occupational safety and health training. Now, few studies are currently exploring the impact and feasibility of current education and training policies on disaster reduction trends in the next few years. Thus, this study tried to use data on occupational disasters from the Ministry of Labor and Occupational Safety and Health Administration in Taiwan and the number of classes and participants in education and training each year to explore the relevance between the current education and training model and the trend of disasters.

In order to have an in-depth understanding of the development trends and feasible methods and to implement the goal of zero occupational hazards at work, the study targeted the construction industry with a high average number of safety and health labor inspections. The three major indicators of occupational disasters as Disabling Frequency Rate(FR), Disabling Severity Rate(SR), and Frequency Severity Indicator (FSI) are used as parameters.

1.3. Literature Review. Occupational disasters are workers' diseases, injuries, disability, or death caused by buildings, machinery, equipment, raw materials, materials, chemicals, gases, vapors, dust, etc. or other working activities in the workplace (from OSHA). According to the Occupational Disaster Statistics Note [2] of the OSHA, there are 17 types of occupational disasters including falling, collision, object flying, object collapsing, being hit, caught, stepped on, contact with high/low temperature, contact with harmful objects, induction, explosion, object rupture, fire, improper action, and traffic accident. The falling has the highest ratio, up to 60% among the types of accidents in construction [5]. The main cause of occupational disasters is usually unsafe behavior and an unsafe working environment [6]. According to the report of the Ministry of Labor on major occupational accidents, more than 67% of injured workers usually did not receive relevant occupational safety training. More than 40% are in the construction industry among the deaths caused by occupational disasters [7]. Obviously, there are still opportunities for improvement in occupational safety in Taiwan. Therefore, exploring the status of occupational disasters in Taiwan's industries and the effects of working inspections and safety training are very important studies to prevent the occurrence of disasters and to reduce the trend of injury.

According to OSHA [2], the degree of occupational disasters can be expressed as disabling injuries. That is, workers suffer occupational injuries in the workplace, causing temporary or permanent loss of basic ability to work and resulting in the inability to continue working. For the number of lost days of the job, there is at least one day. Important indicators of disability injury include FR, SR, and FSI. FR and SR mean the number of disability injuries per million working hours and the number of days lost per million working hours. FSI can reflect both FR and SR. Therefore, FSI is obviously a comprehensive indicator of total disability injury. For example, in the construction, manufacturing wholesale and retail industries, they had shown the development trend of the three indicators in the past 10 years as the figure from OSHA [2] as shown in Figures 1–3. The common types of occupational accidents in the three major industries of construction, manufacturing, wholesale, and retail include (1) falling, (2) traffic accidents, (3) cuts, cuts, or scratches, and (4) being trapped. Thus, it shows that major occupational injury is falling.

In order to estimate and predict the future state, many forecasting methods often require a large amount of stable data, such as time series methods, neural networks, and a large amount of historical data to accurately estimate parameters. In addition, even though linear regression can use a small amount of data to estimate the relevant parameters, it is too simple and the accuracy of the prediction results is not satisfactory. The expert system needs to provide actual empirical rules and a large amount of historical data to get better predictions. However, grey theory can effectively deal with "uncertainty," "multivariate input," "discrete data," and "incomplete data," and can use its predictive value [8]. It was proposed by Professor Julong Deng of Huazhong University of Science and Technology in Mainland China in the early 1980s, and an incomplete message is the essential feature of the grey system as a tool for considering its structure, operation mechanism, and behavior criteria being lacking [9]. Grey information is one kind of uncertain information, and a system with grey information is called a grey system. This theory has been utilized widely in researches, such as system controlling, forecasting, data clustering, decision-making, and others, and many successful applications in a variety of fields such as economics, agriculture, earthquakes, medicine, industry, and control. Therefore, it is proposed as a way to deal with poor, incomplete, or uncertain problems and can be well applied to forecasting and decision-making [10].

Up to now, grey prediction is one of the best features in grey theory and is a prediction result from the grey model. Due to the lack of data, people just only use some observation in a short range of time to predict future data and rapid response. Grey prediction model is the most expansively way to apply for forecasting numerical data scales based on the single time series data [11]. The grey model is summarized into two steps; the first step is grey generating to reduce random original data flow. It has four methods including accumulated generating operation (AGO), Inverse Accumulated Generating Operation (IAGO), Interpolation Generating, and Grey Relational Generating Operation (GRGO). The other step is grey model construction to find out how the sequence forecasted the movement, and it includes GM (1,1), GM (1,N), and GM(0,N). Another problem is how to minimize forecasting error and forecast trending from scale information, and GM (1,1) can make a good prediction for a future time. GM (1,1) is the most

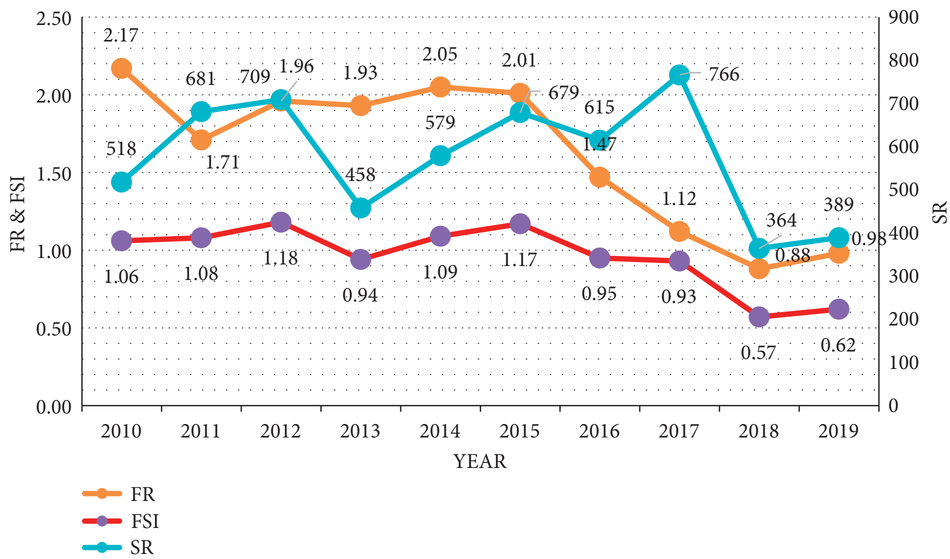

Figure 1: The trend of the three indicators in construction (2010–2019).

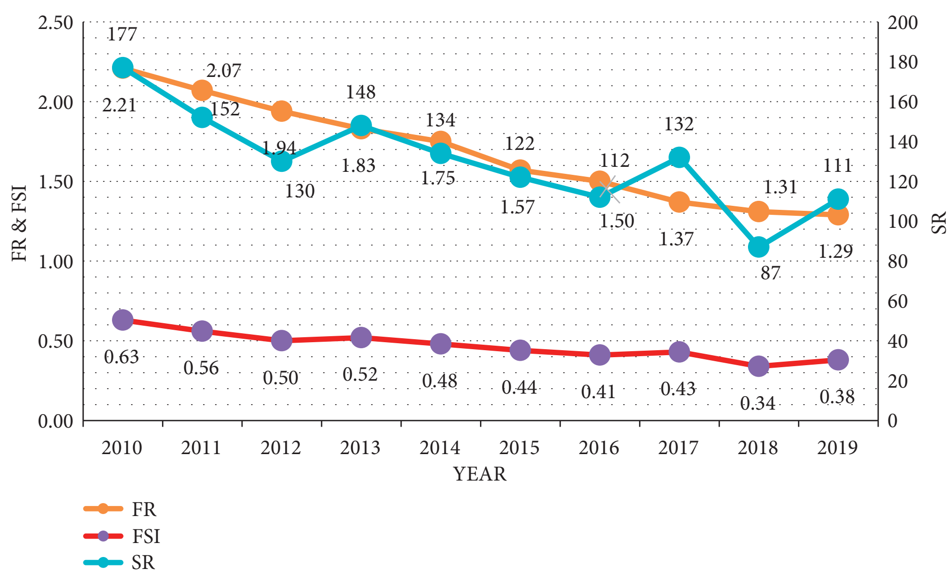

Figure 2: The trend of the three indicators in manufacturing (2010–2019).

popular prediction model in grey system theory, and it not only makes the original information fit but also solves the hassle of overshoot and nonconcentrate. Thus, GM (1,1) is applied to forecasting data from existing actual provided data.

Grey model has been employed for forecasting such as to propose a novel seasonal grey model to predict solar energy consumption in the United States from 2005 to 2017 [12], to forecast the investment performance [13], and to eliminate noise effectively, acquire the optimal wear characteristics of tools and discriminate, and predict the wear state of tools accurately [14]. In addition, the grey model is used to construct a more accurate and stable model to predict the real-time remaining useful life of aircraft engines [15]. In model construction, this study takes GM (1,1) model based on AGO and then goes to grey forecast including sequence grey forecast, seasonal calamities grey forecast, calamities grey forecast, and topological grey forecast. Sequence grey forecast is based on the GM (1,1) model and predicts the time series of existing data, and it is the most basic and simple forecast model.

The grey system currently includes grey generation, grey correlation analysis, grey prediction, grey model, grey decision-making, and grey control [16]. For reducing randomness, increasing the regulation of information, and providing the center information to the model, grey generating is a regular way to find data processing for replenishing information. The study takes the AGO method to accumulate data. Furthermore, it is necessary to check whether the sequences can reflect the regular and useful

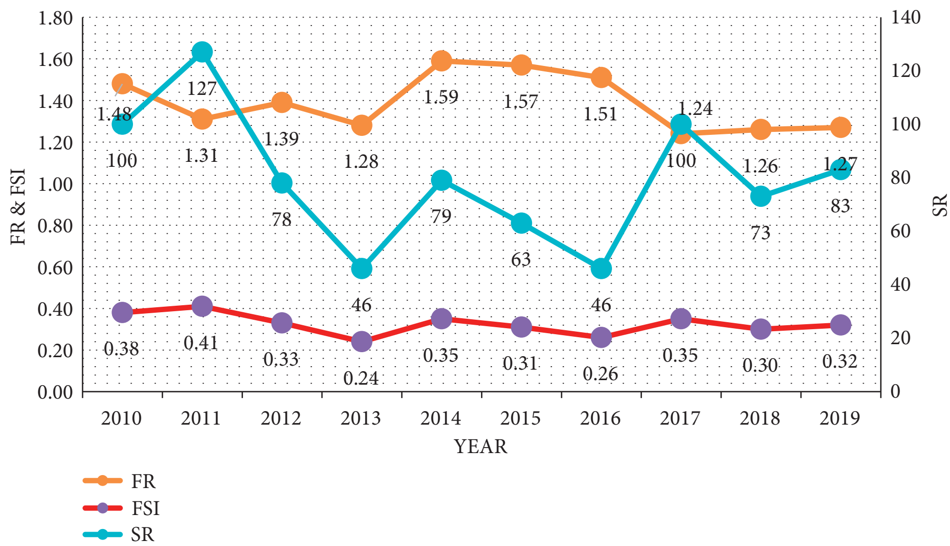

Figure 3: The trend of the three indicators in wholesale and retail (2010–2019).

information. For establishing a grey difference function with generating data, the grey model (1,1) checks whether the sequences are positive or not as well as the dynamic random of sequences [17]. For work safety, they analyze the dynamic situation and future trends of work safety with the GM (1,1) model such as [17–19].

1.4. Research Purpose and Significance. Constructing a high precision model is important for occupational disasters, but some developed grey forecasting models still can not overcome the problems of this research.

GM (1, 1) of the grey model is the most widely used in the literature and is a time series forecasting model. The differential equations of the GM (1, 1) model have time-varying coefficients and represent the first rank differential, and the model is renewed as the new data become available to the prediction. In this study, grey models can be used to forecast the future values of the primitive data points. To increase the accuracy of the GM(1,1) model, this study proposes a rolling GM(1,1) model for three major industries. This study focuses on analyzing and evaluating the trends and related dynamic behaviors of occupational disasters in the three major industries and using the results and predictions to establish the best strategies for planning and forecasting as a reference. Thus, GM (1,1) of the grey theory is used to establish a rolling forecast model and further forecast the trend of disability injuries from occupational disasters from 2020 to 2025 through historical practical data and provides the reference for the Ministry of Labor and related enterprises. The purpose of the study is described as follows.

(1) To analyze the data on the top three industries with the highest average number of inspections (construction, manufacturing, wholesale, and retail industries) and evaluate the dynamic behaviors that are related to the relationships between FR, SR, and FSI

(2) To utilize grey theory and GM (1,1) to establish a rolling forecast model with the highest accuracy rate in the prediction

(3) To further predict the trend of disability injuries in the next six years based on the optimized GM (1,1) rolling model and assess the influences on education and training policies to the downward trend of occupational disasters from the three major industries

Thus, this research constructs a GM (1,1) rolling model for forecasting and uses "residual analysis" and "Mean Absolute Percentage Error (MAPE) sequence judgment." It not only objectively chooses the best GM (1,1) rolling prediction model but also improves the prediction ability and accuracy of this model. There is always a difference between the actual or real and the predicted or forecast value. Forecast accuracy is a measure of how close the actual demand is to the forecast quantity. Regarding forecasting accuracy, MAPE is a measure of the forecast error and the level of demand, which is very useful in forecasting performance. When its value is small, the predicted value is usually close to the actual value. In this study, MAPE for measuring the forecast error is adopted.

2. Methodology

2.1. Data Sets. The design of this study is based on grey theory and taken the data on the top three industries with the highest average number of inspections from 2010 to 2019, such as construction, manufacturing, wholesale, and retail industries, with the highest average number of labor inspections. The framework includes five major procedures which analyze the actual data such as FR, SR, and FSI from 2010 to 2018, which are "data collection and induction," "rolling forecast models establishment," "errors inspection," "the best grey prediction model construction," and "the future value prediction".

About the procedure "data collection and induction," there are 2,932 occupational disasters in the construction industry from 2010 to 2019. They are stumble (17.07%), traffic accidents (16.81%), cuts (16.11%), caught (11.52%), objects fly down (7.41%), hit (6.93%), falling (5.81%), etc. There are 56,581 occupational disasters in the manufacturing industries and it is different from the severity of the construction industries. They are stumbled (27.06%), caught (19.53%), cut (14.80%), improper action (6.99%), hit (6.28%), traffic accident (4.23%), contact with high/low temperature (4.10%), etc. In wholesale and retail industries, there are 7,872 occupational disasters, and they are caught (22.62%), cut (22.00%), stuck (8.93%), hit (8.58%), improper action (7.09%), traffic accident (6.22%), collision (5.37%), etc., shown in Figures 4(a)–4(c). Data collection is an important basic work to develop the grey model, and other procedures are necessary to complete the analysis for prediction as follows.

2.2. GM (1,1) Model to Predicting. In order to deal with the small data sets, the grey model can be employed for limited information. On the other hand, GM (1,1) has been utilized as a predictive model in many fields and represents the first-order one-variable grey model. Some studies have improved grey forecasting models to enhance forecasting accuracy. The method of this research uses grey theory to construct a GM (1,1) rolling model for prediction, and it not only can objectively select the best GM (1,1) rolling forecasting model but also improve the forecasting ability and accuracy through "residual analysis" and "MAPE" with sequence judgment.

Grey generating is for replenishing information to try to reveal the covered regulations or characteristic features from the disordered and unsystematic data. The purposes of grey generating are to reduce the randomness, increase the regulation of information, and provide the center information to the model. First, it inputs original time series data to create the primitive series as Step 1 (input original time series data). In order to smooth the randomness, it uses accumulated generating operation (AGO) to process data as Step 2 (generate time series data AGO formation). For increasing the prediction accuracy of the GM (1,1), an AGO is applied to the time series data. GM (1, 1) type of grey model is the most widely used in the literature and is solved to obtain the n-step ahead predicted value of the system and can then be constructed using a grey differential equation. The calculate work in this model is to find the value of the sequence parameters for predicting the realistic factors as follows: Step 3~Step 7 (generate partial series data, calculate coefficient, construct equation, residual checking, and evaluate the accuracy with MAPE). MAPE is often used to measure forecasting accuracy and usually expresses accuracy as a percentage. Smaller MAPE value indicates better forecasting ability, and it means the result of forecasting ability (if MAPE <10 is excellent; 10~20 is good; 20~50 is reasonable; >50 is poor) [20].

The GM (1,1) rolling model constructing process for forecasting is as follows: (1) Input original time series data; (2) Generate time series data AGO formation; (3) Generate partial series data; (4) Calculate coefficient p and q with least squares method; (5) Construct GM (1,1) forecasting equation; (6) Residual checking; (7) Evaluate the accuracy with MAPE. The grey model prediction is developed as shown in Figure 5. For the steps of the grey GM(1,1) rolling forecast model, it takes the original data of FS in the whole industry from 2010 to 2019 to analysis on $K = 4$ with a total of 7 iterations. Each iteration has 6 steps as follows (Figure 5), explained with the first step, and the others have the same producers. The result of the sample is shown in Table 1.

Step 1: input original time series data $\alpha^{(0)}$.

$$\begin{aligned}\alpha^{(0)}(u) &= \left[\alpha^{(0)}(1), \alpha^{(0)}(2), \alpha^{(0)}(3), \alpha^{(0)}(4)\right] \\ &= [1.96, 1.83, 1.72, 1.66].\end{aligned} \tag{1}$$

Step 2: generate time series data $\alpha^{(1)}(1)$ from $\alpha^{(0)}$ by AGO formation.

$$\begin{aligned}\alpha^{(1)}(u) &= \left[\alpha^{(1)}(1), \alpha^{(1)}(2), \alpha^{(1)}(3), \alpha^{(0)}(4)\right] \\ &= [1.96, 3.79, 5.51, 7.17].\end{aligned} \tag{2}$$

Step 3: generate partial series data $\theta^{(1)}(u)$ from $\alpha^{(1)}(u)$.

$$\theta^{(1)}(u) = \left[\theta^{(1)}(2), \theta^{(1)}(3), \theta^{(1)}(4)\right] = [2.875, 4.650, 6.340]. \tag{3}$$

Step 4: calculate coefficient p and q with least squares method.

$$\begin{aligned}\widetilde{B} &= \begin{bmatrix}\alpha^{(0)}(2) \\ \alpha^{(0)}(3) \\ \alpha^{(0)}(4)\end{bmatrix}, \\ \widetilde{M} &= \begin{bmatrix}-\theta^{(1)}(2) & 1 \\ -\theta^{(1)}(3) & 1 \\ -\theta^{(1)}(4) & 1\end{bmatrix}, \\ \widetilde{W} &= \begin{bmatrix}p \\ q\end{bmatrix}, \\ \widetilde{B} &= \widetilde{M} \cdot \widetilde{W} \Rightarrow \begin{bmatrix}1.83 \\ 1.72 \\ 1.66\end{bmatrix}, \\ &= \begin{bmatrix}-2.875 & 1 \\ -4.650 & 1 \\ -6.340 & 1\end{bmatrix} \cdot \begin{bmatrix}p \\ q\end{bmatrix}.\end{aligned} \tag{4}$$

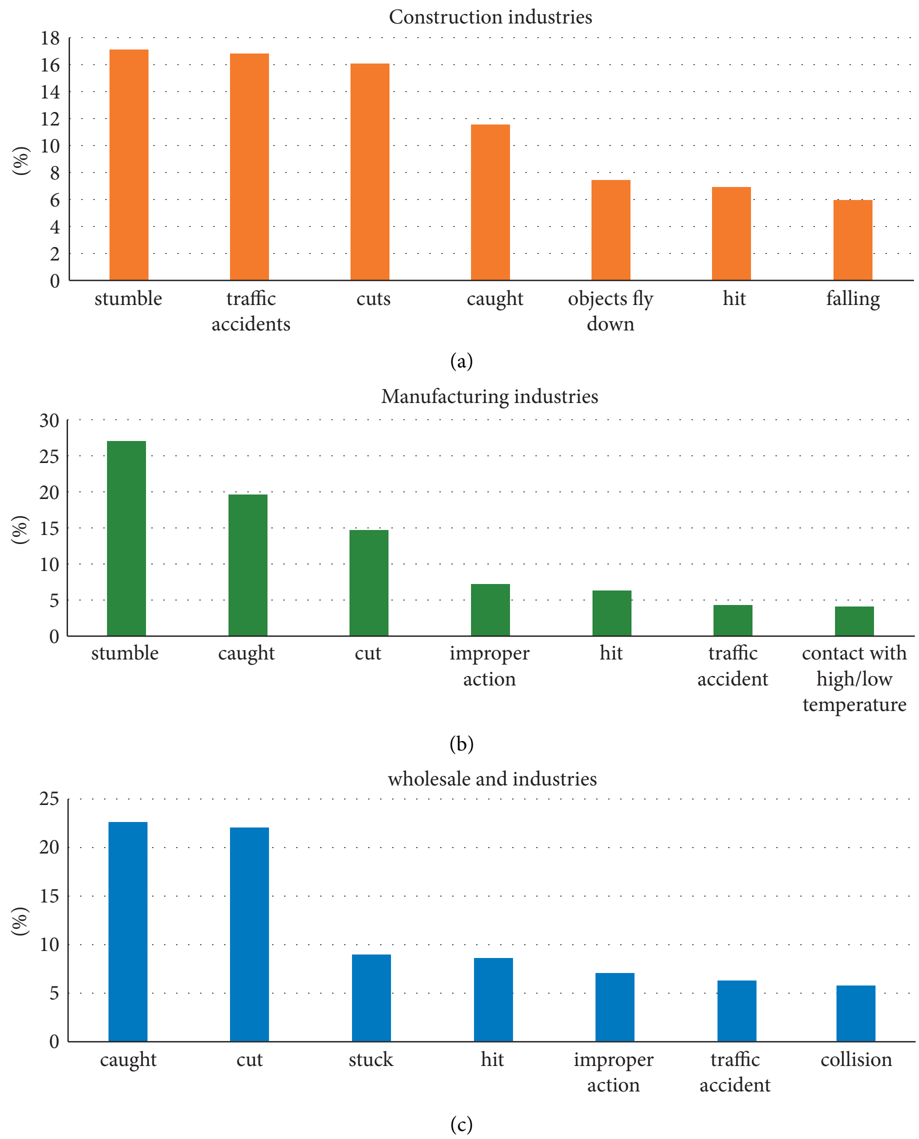

Figure 4: The various disasters of three industries (from [2]): (a)construction industries, (b)manufacturing industries, and (c)wholesale and retail industries.

Step 5: construct GM (1, 1) forecasting equation.

$$\widetilde{W}=\left(\widetilde{M}^{T}\widetilde{M}\right)^{-1}\cdot\widetilde{M}^{T}\cdot\widetilde{B}=\begin{bmatrix}p\\q\end{bmatrix}$$
$$=\begin{bmatrix}0.167 & 0.770\\0.770 & 3.891\end{bmatrix}\cdot\begin{bmatrix}-2.875 & -4.650 & -6.340\\1 & 1 & 1\end{bmatrix}\cdot\begin{bmatrix}1.83\\1.72\\1.66\end{bmatrix}$$
$$=\begin{bmatrix}0.049\\1.964\end{bmatrix}. \tag{5}$$

$p=0.049$, $q=1.964$.

Step 6: residual checking.

GM (1, 1) rolling model:

$$\widehat{\alpha}^{(0)}(u+1)=\left(1-e^{p}\right)\left[\alpha^{(0)}(1)-\frac{q}{p}\right]e^{-pu},\quad \forall u=1,2,3,4$$
$$\Rightarrow\widehat{\alpha}^{(0)}(u+1)=\left(1-e^{0.049}\right)\left[\alpha^{(0)}(1)-\frac{1.964}{0.049}\right]e^{-0.049u},$$
$$\forall u=1,2,3,4. \tag{6}$$

Residual test:

Residual $\varepsilon(u)=|\alpha^{(0)}(u)-\widehat{\alpha}^{(0)}(u)/\alpha^{(0)}(u)|*100\%$

Average $\overline{\varepsilon}=1/4-1*[\sum_{u=2}^{4}|\varepsilon(u)|]*100\%$

Accuracy (ω) test:

Accuracy $\omega=(1-|\varepsilon|)*100\%$

Average accuracy. $\omega=(1-\overline{\varepsilon})*100\%$

Step1: Input original time series data $\boldsymbol{\alpha}^{(0)}$

$\alpha^{(0)} = [\alpha^{(0)}(1), \alpha^{(0)}(2), \alpha^{(0)}(3), \dots, \alpha^{(0)}(u)]$, $\forall\ u = 4,5,6,\dots,n$

Step 2: Generate time series data $\boldsymbol{\alpha}^{(1)}$ from $\boldsymbol{\alpha}^{(0)}$ by AGO formation

$\alpha^{(1)} = [\ \sum_{u=1}^{1} \alpha^{(0)}(u)\ ,\ \sum_{u=1}^{2} \alpha^{(0)}(u)\ , \dots, \sum_{u=1}^{n} \alpha^{(0)}(u)]$, $\forall\ u = 1,2,3,\dots,n$

Step 3: Generate partial series data $\boldsymbol{\theta}^{(1)}(\boldsymbol{u})$ from $\boldsymbol{\alpha}^{(1)}$

$\theta^{(1)}(u) = \frac{\alpha^{(1)}(u)+\alpha^{(1)}(n-1)}{2}$, $\forall\ u = 2,3,4,\dots,n$

$\theta^{(1)} = [\theta^{(1)}(2), \theta^{(1)}(3), \theta^{(1)}(4), \dots, \theta^{(1)}(u)]$, $\forall\ u = 2,3,4,\dots,n$

Step 4: Calculate coefficient p and q with least squares method

$$p = \frac{\left[\sum_{u=2}^{n} \theta^{(1)}(u)\right]\cdot\left[\sum_{u=2}^{n} \alpha^{(0)}(u)\right] - (n-1)\left[\sum_{u=2}^{n} \theta^{(1)}(u)\alpha^{(0)}(u)\right]}{(n-1)\left\{\sum_{u=2}^{n} \left[\theta^{(1)}(u)\right]^2\right\} - \left[\sum_{u=2}^{n} \theta^{(1)}(u)\right]^2}$$

$$q = \frac{\left\{\sum_{u=2}^{n} \left[\theta^{(1)}(u)\right]^2\right\}\left\{\sum_{u=2}^{1} \alpha^{(0)}(u)\right\} - \left\{\sum_{u=2}^{n} \theta^{(1)}(u)\right\}\left\{\sum_{u=2}^{h} \left[\theta^{(1)}(u)\right]\left[\alpha^{(0)}(u)\right]\right\}}{(n-1)\left\{\sum_{u=2}^{n} \left[\theta^{(1)}(u)\right]^2\right\} - \left[\sum_{u=2}^{n} \theta^{(1)}(u)\right]^2}$$

Step 5: Construct GM (1, 1) forecasting equation

$$\hat{\alpha}^{(0)}(u+1) = (1-e^{p})\left[\alpha^{(0)}(1) - \frac{q}{p}\right]e^{-pu}$$

Step 6: Residual checking

GM (1, 1) rolling model $\quad \hat{\alpha}^{(0)}(u+1) = (1-e^{p})\left[\alpha^{(0)}(1) - \frac{q}{p}\right]e^{-pu}$

Residual $\varepsilon(u) = \left|\frac{\alpha^{(0)}(u) - \hat{\alpha}^{(0)}(u)}{\alpha^{(0)}(u)}\right| * 100\%$

Average $\bar{\varepsilon} = \frac{1}{4-1} * [\sum_{u=2}^{4} |\varepsilon(u)|] * 100\%$

Step 7: Evaluate the accuracy with MAPE

Accuracy $\omega = (1 - |\varepsilon|) * 100\%$

MAPE $= \frac{1}{n} * \left\{\sum_{u=1}^{n} \left|\frac{\hat{\alpha}^{(0)}(u) - \alpha^{(0)}(u)}{\alpha^{(0)}(u)}\right|\right\} * 100\%$

Figure 5: The procedures of GM (1, 1) rolling model prediction.

Table 1: The sample of residual checking.

Year	u	Actual	Predictive	|Residual| (%)	Accuracy (%)	Average |Residual| (%)	Average accuracy (%)
2010	$u = 1$	1.960	-	-	-		
2011	$u = 2$	1.830	1.822	0.417	99.583		
2012	$u = 3$	1.720	1.735	0.868	98.132	0.595	99.405
2013	$u = 4$	1.660	1.652	0.501	99.499		
GM (1, 1) rolling model $\hat{\alpha}^{(0)}(u+1) = (1 - e^{0.049})[\alpha^{(0)}(1) - \frac{1.964}{0.049}]e^{-0.049u}$							

3. Simulation Results and Findings

3.1. Data Collection. From 2010 to 2019, the number of industries in Taiwan has increased from 646 to 1,096, the number of employees has grown from 67,293 to 127,001, and the total working hours are from 145,226,132 to 258,917,998. However, the number of disability injuries has shown a downward trend from 315 to 256, and the range of FR is from 1.26 to 1.96. In view of this, it uses literature analysis to understand FR, SR, and FSI in Taiwan (from the reports of OSHA in Taiwan 2020) and collect practical data on the three major indicators of disability injuries from 2010 to 2019. It also applies GM (1,1) rolling model to establish a predictive model to improve the predictive ability and predicts the future trend of occupational disability injuries from 2020 to 2025.

From 2010 to 2019, the number of companies increased from 646 to 1,096, employed people increased from 67,293 to 127,001, the total working hours increased from 145,226,132 to 258,917,998 and disability injuries has shown a downward trend from 315 to 256 (the range of FR is 2.17 to 0.88) in construction. On the other hand, the number of companies increased from 7,949 to 9,846 in the manufacturing industry, workers are from 1,412,552 to 1,802,426, the total working hours are from 3,015,517,387 to 3,641,896,940, and disability injuries are from 6,661 to 4,729 (the range of FR is 2.21 to 1.29). In the wholesale and retail industry, companies increased from 1,178 to 2,562, workers increased from 202,482 to 437,057, the total working hours from 413,460,215 to 857,967,739, and disability injuries are from 611 to 1,091 (the range of FR is 1.24 to 1.59) that showed an upward trend. The three major industries from 2010 to 2019 are shown in Table 2.

3.2. Parameters Design. The GM (1,1) rolling model is used to predict the FR of the construction industry in 2019, and the actual value is 0.98. It shows that the periods as K4 and K9 have predicted values of 0.673 and 1.174 as shown in Tables 3 and 4. It can be seen that the K7 model can effectively predict FR in 2019. In order to further understand the forecast of FR in the other two industries in 2019, the study also uses the actual values from 2012 to 2018 as the model analysis and summarizes the results as shown in Table 5. The study found that the GM (1,1) rolling model predicts the effective forecast FR in 2019, which is K7 (MAPE = 12.402%) in the construction industry, K5 (MAPE = 0.906%) in the manufacturing industry, and K6 in the wholesale and retail industry (MAPE = 3.950%). Thus, we can get the best GM (1,1) rolling model of FR in three industries which are as follows and shown in Table 6.

(1) $\widehat{\alpha}^{(0)}(u+1) = (1-e^{0.1423})[\alpha^{(0)}(1) - 2.6304/0.1423]e^{-0.1423u}$ for the construction industry

(2) $\widehat{\alpha}^{(0)}(u+1) = (1-e^{0.0633})[\alpha^{(0)}(1) - 1.7376/0.0633]e^{-0.0633u}$ for the manufacturing industry

(3) $\widehat{\alpha}^{(0)}(u+1) = (1-e^{0.0683})[\alpha^{(0)}(1) - 1.7796/0.0683]e^{-0.0683u}$ for the wholesale and retail industry.

To predict SR, it uses the same analysis method to obtain forecast accuracy in 2019. Based on the actual values from 2012 to 2018 as the model analysis, it summarizes the results as shown in Table 7. The study found that the model predicts the effective forecast SR in 2019, which is K5 (MAPE = 18.442%) in the construction industry, K9 (MAPE = 8.050%) in the manufacturing industry, and K6 in the wholesale and retail industry (MAPE = 22.754%). The best GM (1,1) rolling model of SR in three industries is as follows.

(1) $\widehat{\alpha}^{(0)}(u+1) = (1-e^{0.1174})[\alpha^{(0)}(1) - 827.8527/0.1174]e^{-0.1174u}$ for the construction industry

(2)$\widehat{\alpha}^{(0)}(u+1) = (1-e^{0.0516})[\alpha^{(0)}(1) - 164.3106/0.0516]e^{-0.0516u}$ for the manufacturing industry

(3) $\widehat{\alpha}^{(0)}(u+1) = (1-e^{-0.0369})[\alpha^{(0)}(1) + 64.0304/0.0369]e^{+0.0369u}$ for the wholesale and retail industry.

To predict FSI based on the actual values from 2012 to 2018, it summarizes the results as shown in Table 8. The study found that the model predicts the effective forecast FSI in 2019, which is K5 (MAPE = 8.283%) in the construction industry, K8 (MAPE = 4.635%) in the manufacturing industry, and K5 in the wholesale and retail industry (MAPE = 9.324%). The best GM (1,1) rolling model of FSI in three industries is as follows.

(1) $\widehat{\alpha}^{(0)}(u+1) = (1-e^{0.2164})[\alpha^{(0)}(1) - 1.3624/0.2164]e^{-0.2164u}$ for the construction industry

(2) $\widehat{\alpha}^{(0)}(u+1) = (1-e^{0.0573})[\alpha^{(0)}(1) - 0.5731/0.0573]e^{-0.0573u}$ for the manufacturing industry

(3) $\widehat{\alpha}^{(0)}(u+1) = (1-e^{-0.0197})[\alpha^{(0)}(1) + 0.2863/0.0197]e^{+0.0197u}$ for the wholesale and retail industry.

3.3. Predictive Analysis on the Best GM (1,1) Rolling Model. On the optimized model of the construction industry as Table 9, FR can obtain the best prediction at K7 (MAPE 12.402%, accuracy 95.235%), SR at K5 (MAPE 18.442%, accuracy 84.739%), and FSI at K5 (MAPE 8.283%, accuracy 87.758%). In manufacturing, the best prediction of FR is at K5 (MAPE 0.906%, accuracy 94.853%), SR at K9 (MAPE 8.050%, accuracy 90.182%), and FSI at K8 (MAPE 4.635%, accuracy 92.658%). In wholesale and retail, the best prediction of FR is at K6 (MAPE 3.950%, accuracy 91.599%), SR at K6 (MAPE 22.745%, accuracy 97.004%), and FSI at K5 (MAPE 9.324%, accuracy 99.909%). Although the GM (1,1) forecasts well in a small data set, this study constructs a prediction model for the three major industries. The average MAPE is 13.042% in the construction industry (MAPE = 10~20 is good), 4.530% in the manufacturing industry (MAPE <10 is excellent), and 12.009% in the wholesale and retail industry (MAPE = 10~20 is good). That means the proposed models predict with greater accuracy and reliability as a qualified prediction model. It further predicts the three major indicators from 2020 to 2025.

Through the best GM (1,1) rolling model, the predicted values of the indicators on disability injuries for the three major industries in 2020–2025 can be presented, respectively, as described in Table 10. According to the results, it can be found that the prediction of FR, SR, and FSI are all present downtrends, as shown in Figures 6–8.

For predicting a continuous dependent variable, linear regression analysis could get better results in a short-term forecast. This research used linear regression after the grey prediction model to show the trend as the same forecast. It found the results of GM(1,1) are more accurate, and all R^2 of FR, SR, and FSI are greater than 0.9 which means predictions fit the data as the model. Thereby, it verified the rationality of the prediction model in this study.

3.4. The Result of Implementation. The results of the study found that the construction industry has the highest

Table 2: The trend of occupational disability injury from 2010 to 2019.

Year	FR			SR			FSI		
	C	M	W&R	C	M	W&R	C	M	W&R
2010	2.17	2.21	1.48	518	177	100	1.06	0.63	0.38
2011	1.71	2.07	1.31	681	152	127	1.08	0.56	0.41
2012	1.96	1.94	1.39	709	130	78	1.18	0.50	0.33
2013	1.93	1.83	1.28	458	148	46	0.94	0.52	0.24
2014	2.05	1.75	1.59	579	134	79	1.09	0.48	0.35
2015	2.01	1.57	1.57	679	122	63	1.17	0.44	0.31
2016	1.47	1.50	1.51	615	112	46	0.95	0.41	0.26
2017	1.12	1.37	1.24	766	132	100	0.93	0.43	0.35
2018	0.88	1.31	1.26	364	87	73	0.57	0.34	0.30
2019	0.98	1.29	1.27	389	111	83	0.62	0.38	0.32

Note. 1. C means "construction industry"; M means "manufacturing industry"; W means "wholesale and retail industry". 2. The data are from the reports of [2] in Taiwan.

Table 3: The prediction of FR in construction ($K = 4$).

Year	2016	2017	2018	2019
Actual	1.47	1.12	0.88	0.98
Predictive	1.459	1.127	0.871	0.673
$\vert$Residual$\vert$ (%)	0.783	0.638	1.015	31.306

GM (1,1) model $\widehat{\alpha}^{(0)}(u+1) = (1 - e^{0.2577})[\alpha^{(0)}(1) - 2.1725/0.2577]e^{-0.2577u}$

$p = 0.2577$ $q = 2.1725$

$\vert$Avg. Residual$\vert$ = 0.812% MAPE(K4) = 0.809%

Table 4: The prediction of FR in construction ($K = 9$).

Year	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Actual	2.17	1.71	1.96	1.93	2.05	2.01	1.47	1.12	0.88	0.98
Predictive	—	2.090	1.945	1.809	1.683	1.566	1.457	1.356	1.262	1.174
$\vert$Residual$\vert$%	—	22.215	0.791	6.258	17.885	22.077	0.865	21.064	43.362	19.776

Table 5: The accuracy of FR prediction in construction.

K	4	5	6	7	8	9
Range	2015 to 2018	2014 to 2018	2013 to 2018	2012 to 2018	2011 to 2018	2010 to 2018
Predictive	0.673	0.643	0.775	0.933	1.043	1.174
Residual	31.306	34.347	20.929	4.765	6.388	19.776
MAPE (K)%	0.809	1.780	6.634	12.402	14.022	16.811
Accuracy %	68.694	65.653	79.071	95.235	93.612	80.224
$X(i) = i$	5	6	4	1	2	3
$Y(j) = j$	1	2	3	4	5	6
$Z(\delta) = \delta$	6	8	7	**5**	7	9

① The actual value of FR in 2019 is 0.98.
② Assume that $X(i) = i$ is expressed as the ith order of accuracy (i) value sorted from high to low.
③ Assume that $Y(j) = j$ is expressed as the jth order of MAPE (j) value sorted from low to high.
④ Assume that $Z(\delta) = \delta$ is expressed as the δth order of $Z(\delta)$value sorted from low to high, where $Z = X(i) + Y(j) = i + j$.

accuracy rate in the prediction of FR (95.235% in K7). In addition, FR predictions of the construction, manufacturing, wholesale, and retail industries all show downward trends. About SR, the wholesale and retail industries have a relatively high accuracy rate (97.044% in K6). However, SR prediction shows an upward trend, as shown in Figure 9. For FSI, the wholesale and retail industries are the highest (99.906% in K5), and the predictions of the three industries represent downward trends.

The common types of occupational accidents of the wholesale and retail industry with SR in the past 10 years include (1) falling, (2) traffic accidents, (3) stabbed, cut, or scratched, (4) caught or rolled, (5) being hit, (6) improper

Table 6: The prediction of FR in top three of industries.

Construction ($k = 7$)	Year	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
	Actual	2.17	1.71	1.96	1.93	2.05	2.01	1.47	1.12	0.88	0.98
	Predictive	—	—	—	2.192	1.901	1.649	1.430	1.241	1.076	0.933
	$\lvert \text{Residual} \rvert$ (%)%	—	—	—	13.568	7.262	17.962	2.705	10.761	22.271	4.765
	GM (1,1) model $\widehat{\alpha}^{(0)}(u+1) = (1-e^{0.1423})[\alpha^{(0)}(1) - 2.6304/0.1423]e^{-0.1423u}$										
	$p = 0.1423$ $q = 2.6304$										
	$\lvert \text{Avg.Residual} \rvert = 12.422\%$ MAPE(K7) = 12.402%										
Manufacturing ($k = 5$)	Year	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
	Actual	2.21	2.07	1.94	1.83	1.75	1.57	1.50	1.37	1.31	1.29
	Predictive	—	—	—	—	—	1.576	1.480	1.389	1.304	1.224
	$\lvert \text{Residual} \rvert$ (%)	—	—	—	—	—	0.404	1.360	1.372	0.491	5.147
	GM (1,1) model $\widehat{\alpha}^{(0)}(u+1) = (1-e^{0.0633})[\alpha^{(0)}(1) - 1.7376/0.0633]e^{-0.0633u}$										
	$p = 0.0633$ $q = 1.7376$										
	$\lvert \text{Avg} \cdot \text{Residual} \rvert = 0.907\%$ MAPE(K5) = 0.906%										
Wholesale and retail ($k = 6$)	Year	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
	Actual	1.48	1.31	1.39	1.28	1.59	1.57	1.51	1.24	1.26	1.27
	Predictive	—	—	—	—	1.636	1.528	1.427	1.333	1.245	1.163
	$\lvert \text{Residual} \rvert$ (%)	—	—	—	—	2.877	2.686	5.495	7.490	1.195	8.441
	GM (1,1) model $\widehat{\alpha}^{(0)}(u+1) = (1-e^{0.0683})[\alpha^{(0)}(1) - 1.7796/0.0683]e^{-0.0683u}$										
	$p = 0.0683$ $q = 1.7796$										
	$\lvert \text{Avg.Residual} \rvert = 3.949\%$ MAPE(K6) = 3.950%										

Table 7: The prediction of SR in top three of industries.

K	Year	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Construction ($k = 5$)	Actual	518	681	709	458	579	679	615	766	364	389
	Predictive	—	—	—	—	—	716.999	637.597	566.989	504.200	448.364
	$\lvert \text{Residual} \rvert$ (%)	—	—	—	—	—	5.596	3.674	25.981	38.517	15.261
	GM (1,1) model $\widehat{\alpha}^{(0)}(u+1) = (1-e^{0.1174})[\alpha^{(0)}(1) - 827.8527/0.1174]e^{-0.1174u}$										
	$p = 0.1174$ $q = 827.8527$										
	$\lvert \text{Avg.Residual} \rvert = 18.442\%$ MAPE(K5) = 18.442%										
Manufacturing ($k = 9$)	Actual	177	152	130	148	134	122	112	132	87	111
	Predictive	—	151.245	143.640	136.418	129.559	123.044	116.858	110.982	105.402	100.102
	$\lvert \text{Residual} \rvert$ (%)	—	0.497	10.492	7.826	3.315	0.856	4.337	15.923	21.152	9.818
	GM (1,1) model $\widehat{\alpha}^{(0)}(u+1) = (1-e^{0.0516})[\alpha^{(0)}(1) - 164.3106/0.0516]e^{-0.0516u}$										
	$p = 0.0156$ $q = 164.3106$										
	$\lvert \text{Avg.Residual} \rvert = 8.050\%$ MAPE(K9) = 8.050%										
Wholesale and retail ($k = 6$)	Actual	100	127	78	46	79	63	46	100	73	83
	Predictive	—	—	—	—	66.954	69.470	72.080	74.788	77.598	80.513
	$\lvert \text{Residual} \rvert$ (%)	—	—	—	—	15.248	10.270	56.695	25.212	6.299	2.996
	GM (1,1) model $\widehat{\alpha}^{(0)}(u+1) = (1-e^{-0.0369})[\alpha^{(0)}(1) + 64.0304/0.0369]e^{+0.0369u}$										
	$p = -0.0369$ $q = 64.0304$										
	$\lvert \text{Avg.Residual} \rvert = 22.754\%$ MAPE(K6) = 22.754%										

Table 8: The prediction of FSI in top three of industries.

	Year	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Construction ($k = 5$)	Actual	1.06	1.08	1.18	0.94	1.09	1.17	0.95	0.93	0.57	0.62
	Predictive	—	—	—	—	—	1.182	0.974	0.802	0.661	0.544
	$\lvert \text{Residual} \rvert$ (%)	—	—	—	—	—	1.009	2.473	13.774	15.886	12.242
	GM (1,1) model $\widehat{\alpha}^{(0)}(u+1) = (1-e^{0.2164})[\alpha^{(0)}(1) - 1.3624/0.2164]e^{-0.2164u}$										
	$p = 0.1939$ $q = 1.5115$										
	$\lvert \text{Avg.Residual} \rvert = 8.286\%$ MAPE(K5) = 8.283%										

Table 8: Continued.

	Year	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Manufacturing ($k=8$)	Actual	0.63	0.56	0.50	0.52	0.48	0.44	0.41	0.43	0.34	0.38
	Predictive	—	—	0.526	0.497	0.469	0.443	0.418	0.395	0.373	0.352
	$\vert$Residual$\vert$(%)	—	—	5.169	4.508	2.308	0.640	1.991	8.167	9.676	7.342
	GM (1,1) model $\hat{\alpha}^{(0)}(u+1) = (1-e^{0.0573})[\alpha^{(0)}(1) - 0.5731/0.0573]e^{-0.0573u}$										
	$p=0.0573$ $q=0.5731$										
	$\vert$Avg.Residual$\vert$ $=4.637\%$ MAPE(K8) $=4.635\%$										
Wholesale and retail ($k=5$)	Actual	0.38	0.41	0.33	0.24	0.35	0.31	0.26	0.35	0.30	0.32
	Predictive	—	—	—	—	—	0.296	0.302	0.308	0.314	0.320
	$\vert$Residual$\vert$(%)	—	—	—	—	—	4.498	16.129	12.021	4.680	0.094
	GM (1,1) model $\hat{\alpha}^{(0)}(u+1) = (1-e^{-0.0197})[\alpha^{(0)}(1) + 0.2863/0.0197]e^{+0.0197u}$										
	$p=-0.0197$ $q=0.2863$										
	$\vert$Avg.Residual$\vert$ $=9.332\%$ MAPE(K5) $=9.324\%$										

Table 9: The accuracy of the best GM (1,1) rolling model in three industries.

	FR			SR			FSI		
Industry	C	M	W	C	M	W	C	M	W
K	7	5	6	5	9	6	5	8	5
Predictive	0.933	1.224	1.163	448.364	100.102	80.513	0.544	0.352	0.320
Residual	4.765	5.147	8.441	15.261	9.818	2.996	12.242	7.342	0.094%
MAPE (K)%	12.402	0.906	3.950	18.442	8.050	22.745	8.283	4.635	9.324%
Accuracy %	95.235	94.853	91.559	84.739	90.182	97.004	87.758	92.658	99.906%

Note: C means "construction industry"; M means "manufacturing industry"; W means "wholesale and retail industry".

Table 10: The predicted indicators of disability injuries in 2020–2025.

Industry	Indicators	Year u	2019 10	2020 11	2021 12	2022 13	2023 14	2024 15	2025 16
	FR in K7		0.98	0.74	0.60	0.48	0.39	0.31	0.25
Construction	SR in K5	Prediction	389	305	207	172	143	118	98
	FSI in K5		0.62	0.47	0.39	0.33	0.28	0.24	0.20
	FR in K5		1.29	1.21	1.17	1.12	1.07	1.02	0.98
Manufacturing	SR in K9	Prediction	111	99	93	88	84	79	75
	FSI in K8		0.38	0.33	0.32	0.30	0.29	0.28	0.26
	FR in K6		1.27	1.13	1.08	1.03	0.98	0.94	0.90
Wholesale and retail	SR in K6	Prediction	83	94	101	107	114	122	130
	FSI in K5		0.32	0.33	0.33	0.34	0.35	0.35	0.36

action, and (7) collision. Although FR and FSI are declining, the severity of occurrence is high. Therefore, SR has an upward trend, which is due to the common type of traffic accidents in the retail industry.

The study further proposes that relevant actual disaster cases can be added to the training materials to improve workers' safety awareness of occupational disaster prevention for the occupational disasters in the wholesale and retail industries. In addition, it could further strengthen the communication of occupational safety and health education in the enterprises to reduce SR and protect the safety and health of workers.

3.5. GM(1,2) Correlation Analysis on FR and TR. In addition to predicting the trends of FS, FR, and FSI in three industries and to further understand the relevance of training courses and working accidents for safety, the study tried to find out the feasibility of trend; that is based on the small sample characteristics of grey theory to find out the strength of the correlation between training and accidents. It used grey relational analysis in GM (1,N) model that represents the first rank differential and N number for input the variables, and generally, it is associated variable analysis. That takes FR and TR (Training Rate) as two variables and analyzes their correlation through the difference between these two variables, shown in Table 11. Considering the small and limited amount of data, the usability of trend development on FR/SR/FSI is verified through GM(1,2) correlation analysis. The research uses the following six steps to find relevance.

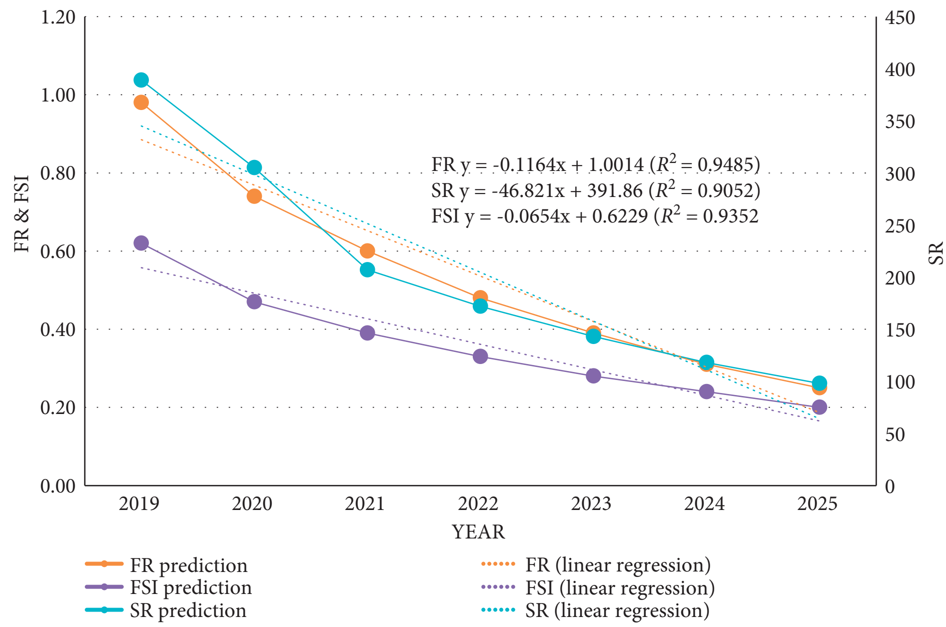

Figure 6: The trend on the best GM (1,1) rolling model in construction.

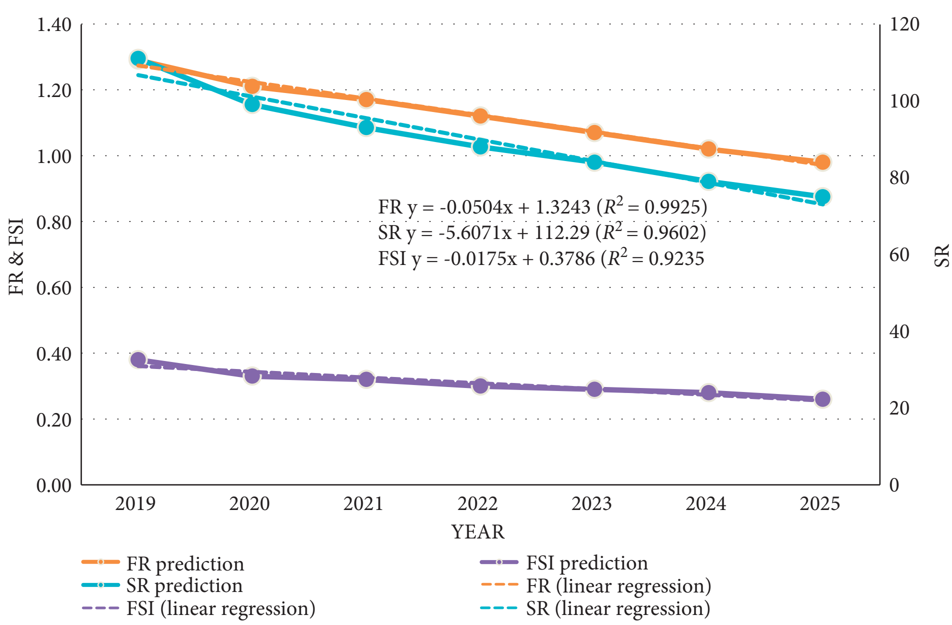

Figure 7: The trend on the best GM (1,1) rolling model in manufacturing.

Step 1: to establish a standard sequence $x_0(k)$. According to Table 11, take the minimum value $x_0(k)$ from each industry's difference.

$$\alpha_0(k) = \{0.47, 0.39, 0.39, 0.59, 0.75, 0.79, 0.46, 0.35, 0.25, 0.03\}. \tag{7}$$

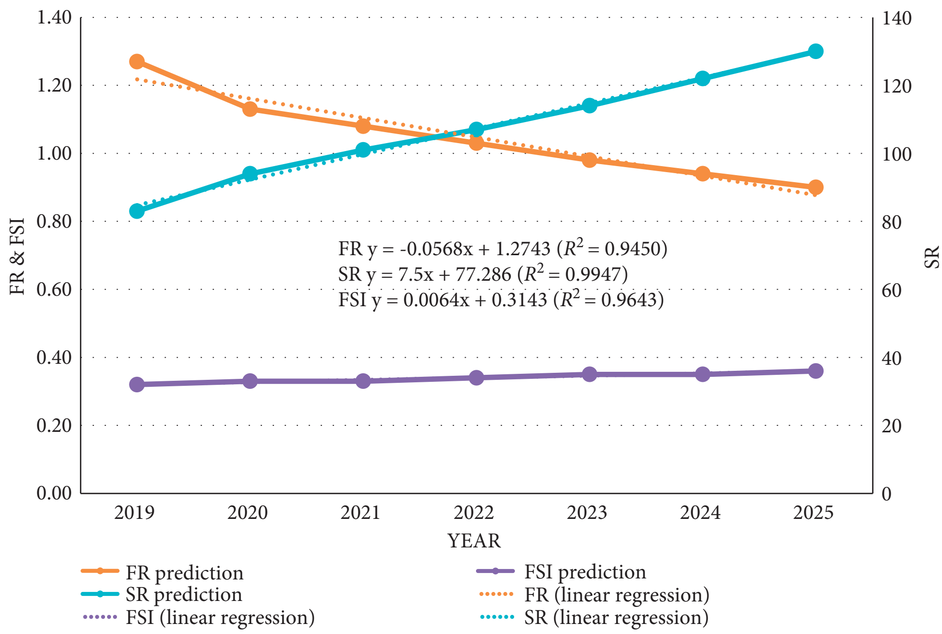

Figure 8: The trend on the best GM (1,1) rolling model in wholesale and retail.

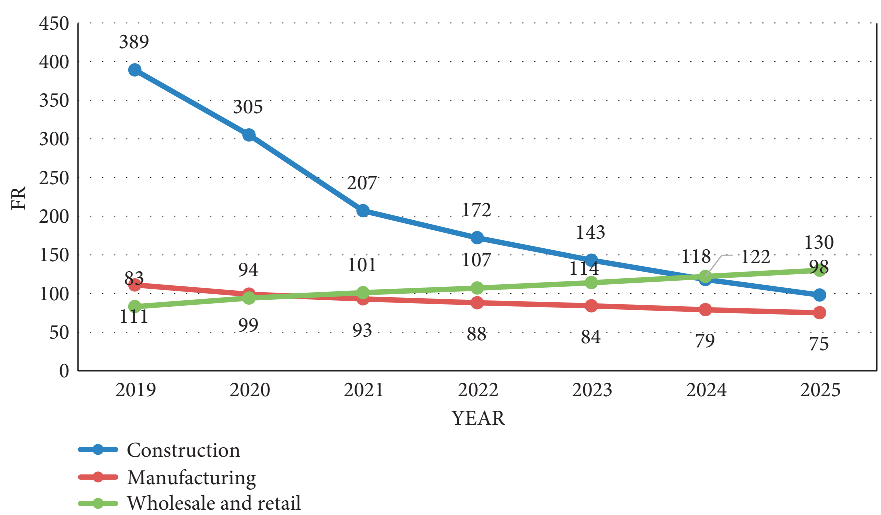

Figure 9: The trend of SR in three industries (2019–2025).

Table 11: FR and TR in top three industries.

Year	Construction			Manufacturing			Wholesale and retail		
	FR	TR	Difference	FR	TR	Difference	FR	TR	Difference
2010	2.17	0.29	1.88	2.21	2.24	−0.03	1.48	0.75	0.73
2011	1.71	0.28	1.43	2.07	2.32	−0.25	1.31	0.80	0.51
2012	1.96	0.31	1.65	1.94	2.29	−0.35	1.39	0.85	0.54
2013	1.93	0.23	1.70	1.83	2.60	−0.77	1.28	0.82	0.46
2014	2.05	0.26	1.79	1.75	2.75	−1.00	1.59	0.80	0.79
2015	2.01	0.48	1.53	1.57	2.70	−1.13	1.57	0.82	0.75
2016	1.47	0.44	1.03	1.5	2.62	−1.12	1.51	0.92	0.59
2017	1.12	0.44	0.68	1.37	2.90	−1.53	1.24	0.85	0.39
2018	0.88	0.49	0.39	1.31	2.64	−1.33	1.26	0.84	0.42
2019	0.98	0.51	0.47	1.29	2.63	−1.34	1.27	0.80	0.47

Note: the data of TR is from the Institute of [2].

Step 2: to establish a sequence of differences in three industries from 2010 to 2019, where $\alpha_1(k), \alpha_2(k)$, and $\alpha_3(k)$ are, respectively, represented as construction, manufacturing industry, and wholesale and retail.

$$\begin{aligned}
\alpha_1(k) &= \{1.88, 1.43, 1.65, 1.70, 1.79, 1.53, 1.03, 0.68, 0.39, 0.47\},\\
\alpha_2(k) &= \{0.03, 0.25, 0.35, 0.77, 1.00, 1.13, 1.12, 1.53, 1.33, 1.34\},\\
\alpha_3(k) &= \{0.73, 0.51, 0.54, 0.46, 0.79, 0.75, 0.59, 0.39, 0.42, 0.47\}.
\end{aligned} \tag{8}$$

Step 3: to calculate $\Delta_{0i}(k)$.

(1) $i = 1$

$$\begin{aligned}
\Delta_{01}(k) &= \left|\alpha_0(k) - \alpha_1(k)\right|, \quad \forall k = 1, 2, 3, 4, 5, 6, 7, 8, 9, 10,\\
\alpha_0(1) &= \{0.47, 0.39, 0.39, 0.59, 0.75, 0.79, 0.46, 0.35, 0.25, 0.03\},\\
\alpha_1(k) &= \{1.88, 1.43, 1.65, 1.70, 1.79, 1.53, 1.03, 0.68, 0.39, 0.47\},\\
\Delta_{01}(1)\left|\alpha_0(1) - \alpha_1(1)\right| &= |0.47 - 1.88| = 1.41,\\
\Delta_{01}(2) &= \left|\alpha_0(2) - \alpha_1(2)\right| = |0.39 - 1.43| = 1.04,\\
\Delta_{01}(3) &= \left|\alpha_0(3) - \alpha_1(3)\right| = |0.39 - 1.65| = 1.26,\\
\Delta_{01}(4) &= \left|\alpha_0(4) - \alpha_1(4)\right| = |0.59 - 1.70| = 1.11,\\
\Delta_{01}(10) &= \left|\alpha_0(10) - \alpha_1(10)\right| = |0.03 - 0.47| = 0.44,\\
\Delta_{01} &= \{1.41, 1.04, 1.26, 1.11, 1.04, 0.74, 0.57, 0.33, 0.14, 0.44\}.
\end{aligned} \tag{9}$$

Max. $\Delta_{01} = 1.41$, Min. $\Delta_{01} = 0.14$, Ave. $\Delta_{01} = 0.808$

(2) $i = 2$

$$\begin{aligned}
\alpha_2(k) &= \{0.03, 0.25, 0.35, 0.77, 1.00, 1.13, 1.12, 1.53, 1.33, 1.34\},\\
\Delta_{02}(1) &= \left|\alpha_0(1) - \alpha_2(1)\right| = |0.47 - 0.03| = 0.44,\\
\Delta_{02} &= \{0.44, 0.14, 0.04, 0.18, 0.25, 0.34, 0.66, 1.18, 1.08, 1.31\}.
\end{aligned} \tag{10}$$

Max. $\Delta_{02} = 1.31$, Min. $\Delta_{02} = 0.04$, Ave. $\Delta_{01} = 0.562$

(3) $i = 3$

$$\begin{aligned}
\alpha_3(k) &= \{0.73, 0.51, 0.54, 0.46, 0.79, 0.75, 0.59, 0.39, 0.42, 0.47\},\\
\Delta_{03} &= \{0.26, 0.12, 0.15, 0.13, 0.04, 0.04, 0.13, 0.04, 0.17, 0.44\}.
\end{aligned} \tag{11}$$

Max. $\Delta_{03} = 0.44$, Min. $\Delta_{01} = 0.04$, Ave. $\Delta_{01} = 0.152$

Step 4: to find the maximum value of Δ_{Max} and the minimum value of Δ_{Min}

$$\begin{aligned}
\Delta_{\mathrm{Max}} &= \mathrm{Max.}\{\mathrm{Max.}\Delta_{0i}\},\\
\Delta_{\mathrm{Min}} &= \mathrm{Min.}\{\mathrm{Min.}\,\Delta_{0i}\} \quad \forall i = 1, 2, 3,\\
\Delta_{\mathrm{Max}} &= \{1.41, 1.31, 0.44\} = 1.41,\\
\Delta_{\mathrm{Min}} &= \{0.14, 0.04, 0.04\} = 0.04.
\end{aligned} \tag{12}$$

Step 5: to solve the grey relation.

(1) $\Gamma[\alpha_0(k), \alpha_1(k)] = \Delta_{\mathrm{Min}} + \Delta_{\mathrm{Max}}/\mathrm{Ave.}\Delta_{01} + \Delta_{\mathrm{Max}} = 0.14 + 1.41/0.808 + 1.41 = 0.699$

(2) $\Gamma[\alpha_0(k), \alpha_2(k)] = \Delta_{\mathrm{Min}} + \Delta_{\mathrm{Max}}/\mathrm{Ave.}\Delta_{02} + \Delta_{\mathrm{Max}} = 0.04 + 1.31/0.562 + 1.31 = 0.721$

(3) $\Gamma[\alpha_0(k), \alpha_3(k)] = \Delta_{\mathrm{Min}} + \Delta_{\mathrm{Max}}/\mathrm{Ave.}\Delta_{03} + \Delta_{\mathrm{Max}} = 0.04 + 0.44/0.152 + 0.44 = 0.811$

Step 6: to compare the relations.

The study found that $\Gamma[\alpha_0(k), \alpha_3(k)] > \Gamma[\alpha_0(k), \alpha_2(k)] > \Gamma[\alpha_0(k), \alpha_1(k)]$. It means that the correlation between FR and TR is the most significant in the wholesale and retail industry, which means that there has an impact on the frequency of working accidents and training hours.

It found that the trend of FS in the wholesale and retail industry is increasing. At the same time, its TR is lower than the other industries. Through grey correlation analysis, it can be known that it has the greatest relevance, and the trend of GM(1,1) can be used as the basis for policy formulation in the government and training enhancement.

4. Conclusions and Future Works

Occupational disasters are direct hazards to laborers at work and indirectly affect the overall social security and national economic development. The prevention system and safety inspection of occupational disasters are the focus for the governments. In recent years, the plans of related occupational disaster reduction have shown good results. However, the serious rate of occupational disasters in Taiwan is still high compared with foreign countries, such as falling in construction industries.

This study uses the statistical data from 2020 to 2018 as original data and takes data in 2010 as the verification group. However, occupational disasters are often affected by the industrial environment such as laws or disaster prevention plans and may cause data changes. Thus, the research scope and limits are based on the current conditions of the three major industries for predicting. In order to maintain the accuracy of the best GM (1,1) model, the forecast value can be updated by rolling update data year by year. It predicts the trend from 2020 to 2025 and shows that Disabling Severity Rate (SR) is an upward trend in the wholesale and retail industries. This shows that government units should regard traffic accidents as the main focus of supervision. It could strengthen safety measures for driving or motorcycles, continue to promote the concept of traffic safety, and conduct regular safety performance inspections. In addition, the trend value in 2020 to 2025 can provide a reference for the Ministry of Labor and related enterprises.

Working inspection is often used for occupational disaster prevention. Through preinspection, it can confirm unsafety situations in the work environment and reduce the probability of disasters happening. The future work will continue to apply grey theory, combine cluster analysis, genetic algorithms, and grey systems, and propose a quantitative prediction model for occupational hazards based on the types, locations, and factors with accidents. The forecast model will focus on the construction and wholesale and retail industry to provide the risk trend as references.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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