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An Optimized Iron Ore Price Forecasting Using Convolutional Neural Network Optimized by Modified Search and Rescue Optimization Algorithm

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ABSTRACT

One of the most widely used metals in the world is the Iron. The world cost of iron ore is defineded by its supply and demand. Numerous variabes such as steel, scrap, oil, gold, interest rate, inflation rate, dollar value, and stock value affect the world price of iron ore. Therefore, for economic investment of iron ore, it should be forecasted precisely by the scientists to give a direction to the decision makers to make a proper decision for the society. Due to the multiplicity of effective parameters and the complexity of the relationships between the iron ore variables, artificial intelligence is the best idea for forecasting. In this paper, we utilized a new optimized version of Convolutional Neural Network (CNN) to facilitate this task. To do so, a modified version of the Search and Rescue (MSAR) optimization algorithm has been designed and used for optimizing the CNN for improving its training efficiency in forecasting the iron ore price volatilities. The method is then validated based on ten different variables. Finally, a comparison of the results with various state of the art techniques was carried out to show the suggested method effectiveness. The results showed that the suggested technique has the fittest results in comparison to the other newest techniques.

Keywords: *Forecasting; iron ore; price volatilities; convolutional neural network; Modified search and rescue (MSAR) optimizer.*

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1. INTRODUCTION

The first and best source of mineral goods is mining that all countries consider necessary to maintain and improve their living standards [1]. Minerals are required for building hospitals, roads, cars, buildings, satellites, and computers, to produce electricity, to supply goods and other services that users benefit from [2]. The most significant factor in the supply of feed to production units is the price of mineral products, which are primarily used as raw materials in different industries [3]. There have been major variations in the prices of minerals and metals for a number of causes, including changes in global political and economic conditions and unforeseen changes in these factors in recent years, resulting in various outcomes from the design process, leading in some cases to end and become industrial units [4]. In recent years, increases in world iron ore prices that have influenced the iron and steel industry can be due to these changes. The raw material for the manufacture of steel is the iron ore, which is utilized to make steel for 79 percent of the iron ore mined worldwide.

The future, on the other hand, belongs to those who properly prepare for it. According to the future forecasting, any effective institution or organization must make the required preparations. There are many ways for this to be done [5]. Such approaches

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can transform past experiences into predicting future occurrences.

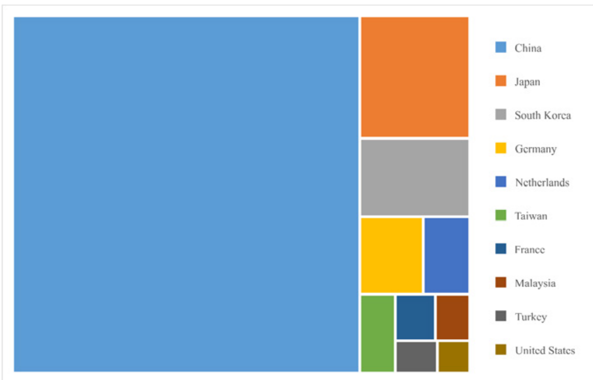
If the forecasting accuracy has been high enough, the risk of the future plan will be decreased, and with high confidence and more money, the investor joins the company, so forecasting and in particular price forecasting has a special place in project evaluation [6]. There are many cost predictions approaches, but the most suitable of these is a technique that nonlinearly and dynamically tests variables, which is closer to fact than other techniques [7]. Literature determined that the cost of iron ore has become an important economic variable that has a strong effect on the world and any uncertainty has a notable influence on both countries of exporting and importing [8].

In Japan, the second-biggest producer of crude steel in the world, the share of iron ore production is too low. This reason forces this country to import and become the world's second-largest importer of stone, concentrate and pellets after China.

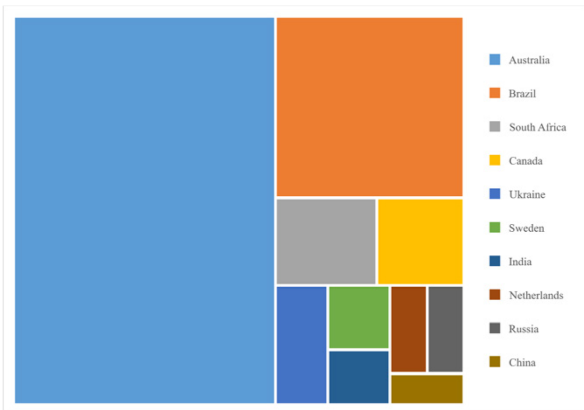
In 2017, Japan imported 72 million and 960 thousand tons of iron ore, concentrate and pellets from Australia, which was equivalent to 57.6% of the country's total imports. In the field of pellets, Brazil was the largest exporter to Japan in 2017, which was the first export of this country with 7 million 671 thousand tons of pellets. About 49% of Japan pellet imports in 2017 were from Brazil. Canada was the second largest exporter of pellets to Japan in 2017, with 3.3 million tons of pellets.

After Brazil and Canada, the United States was the third largest exporter of pellets with 2.7 million tons. The United States did not have a large share of the Japanese pellet market in previous years, but in 2017 it increased its share to 12.7% of this market. Chile, Ukraine, India and Australia were the next largest exporters of this product to Japan. Fig. (1) shows the tree map share profile of the most importer and exporter countries for the iron ore forecasting in 2019. For more clarifications, Table 1 is given to indicate the amount of this case.

Several studies have been done on the fluctuations in iron ore prices. Better import or



(A)



(B)

Fig. 1. The tree map share profile of the most importer (A) and exporter (B) countries for the iron ore forecasting in 2019

Table 1. The Iron ore (A) imports and (B) exports in 2019 (US$)

Rank	Importer	Iron ore imports (US$)	Exporter	Iron ore imports (US$)
1	China	$99,843,052,000	Australia	$65,846,093,000
2	Japan	$10,855,972,000	Brazil	$22,181,780,000
3	South Korea	$6,948,556,000	South Africa	$5,749,280,000
4	Germany	$3,937,065,000	Canada	$4,948,361,000
5	Netherlands	$2,885,752,000	Ukraine	$4,030,612,000
6	Taiwan	$2,260,430,000	Sweden	$2,583,431,000
7	France	$1,507,940,000	India	$2,203,504,000
8	Malaysia	$1,299,014,000	Netherlands	$2,117,740,000
9	Turkey	$1,090,281,000	Russia	$2,090,433,000
10	United States	$842,067,000	China	$1,486,350,000

export can be established by concluding better contracts or offering good prices for the purchase or sale of the iron ore. On the other hand, cost prediction has a significant role in planning and is the basis of economic studies of buying and selling iron ore and creating a market for it [9-11]. Of course, it should be noted that the price of iron ore depends on several factors [12].

Therefore, recently, the researchers work on making better forecasting model to achieve more precise models for helping the decision makers [13, 14]. The inputs in the forecasting models have significant effect on the model accuracy [15, 16]. There are lots if work in this subject, for instance, Ma et al. [17] proposed a best method for iron ore import and usage forecasting of China. The study proposed a hybrid grey model by Particle Swarm Optimizer (PSO) for iron ore prediction in China. Simulation achievements demonstrated that the technique can progress the forecasting precision toward the traditional model [18]. Also, 5-year forecasting was performed for the next five years.

Ramos et al. [19] provided a simulation for the forecasting of the iron ore commodity cost by applying Geometric Brownian Motion (GBM) technique. The model was formed on the time series of the historical cost. Then a comparison of the model with some newest forecasting techniques was carried out. Final results showed that the model has some limitations. Nevertheless, it is general well forecasting tool for the work, if accomplished together with other methods.

Lee et al. [20] presented a methodology technique based on machine learning to forecast of the iron ore price for a month after trading trials. A distributed lag model along with MLP (Multiple-layer perceptron), LSTM (Long short-term memory), and RNN (Recurrent neural network) were used for the forecasting purpose. As stated by the simulations, the comparison results of the models showed the minimum forecasting error for the LSTM. As well, the comparison results showed lower accuracy for the distributed lag and LSTM ensemble model.

Wang et al. [21] analyzed the capability of the nonlinear autoregressive neural network (NARNN), autoregressive integrated moving average (ARIMA), and empirical mode decomposition (EMD) models to combine and give a hybrid technique, called EMD-NARNN-ARIMA. Simulation achievements showed that, in comparison to the NARNN or seasonal SARIMA techniques, the suggested technique has better forecasting accuracy for importing of iron ore to China. The forecasting error for the proposed method is meaningfully lesser comparing that of NAR and SARIMA, however, it does not increment the time- complication.

Another model for reliable monthly iron ore price volatility forecasting was suggested by Ewees et al. [22]. To train the multilayer perceptron neural network, the approach used a different variant of the Grasshopper Optimizer (GO). The model's simulation achievements have been compared with some newest models to demonstrate the efficacy of the process. The achievements demonstrated that the proposed technique was dominant over the others. The major target of this study is to present a new optimized and well-organized procedure for optimal iron ore prices forecasting.

2. CONVOLUTIONAL NEURAL NETWORKS

In various forecasting applications for the years, Artificial Neural Networks (ANN) are regarded as high-performance methodologies, a great deal of work was done to achieve well-organized of these networks [23]. Recently, different configuration of neural networks based on deep learning has been designed [24]. One of the popular kinds of these networks is Convolutional Neural Network (CNN) [25]. This popularity is due to its higher efficiency in complex estimation problems [26]. This network is derived by the key formation of the animals' visual ability.

The membranous neurons in CNN answer to encouragement in restricted regions which is called the *receptive field*. This region partially overlays each neuron till the visual area has been tiled. The response to the motive for all the neurons can be mathematically calculated by a convolution process. The main parts of it are the CNN layers.

For estimation purpose in this study, ten input variables including the inflation rates of US and Japan, the exchange rates of the Japanese Yen (JPY) and the Australian Dollar (AUD), and costs of oil, gold, copper, scrap, and silver and past iron ore costs as the input and the output of the Convolutional layer. Because the equality of the input and output matrices number is not a constraint, to drive the regional characteristics of the base data, local feature extraction is performed.

The learning method obtains several kernel matrices to provide significant characteristics to use in the forecasting. In this case, backpropagation algorithm is a good selection which will be utilized to optimize the connectivity among the network weights. The sliding window creates the convolution in this layer. A vector is then made by the dot product accompanied by adding the weights up and the sliding window.

The Rectified Linear Unit (ReLU) has been used as activation function of the neurons, which can be formulated as follows [27]:

$$f(x) = \max(x, 0) \tag{1}$$

For more output scale reduction, the max pooling has been employed.

Then, the CNN has been optimized for achieving a satisfying fitting with the problem based on internal weights. For instance, Stochastic Gradient Descent, Gradient Descent, Mini-Batch Gradient Descent, with Back Propagation (BP)-base, Adagrad and Momentum [28]. The main duty of BP method is to adjust the neurons weights by minimizing the error of training pairs to give a satisfying fitting with the considered output [29, 30]. Indeed, the BP used the gradient descent technique for this minimization which is formulated below [31]:

$$L = \sum_{j=1}^{\mathrm{N}} \sum_{i=1}^{M} -d_j^{(i)} \log z_j^{(i)} \tag{2}$$

where, z_j and d_j represent the obtained output and the desired vectors for the class number M.

The Softmax function for the CNN is achieved as follows:

$$z_j^{(i)} = \frac{e^{f_j}}{\sum_{i=1}^{M} e^{f_i}} \tag{3}$$

where, M describes the number of samples.

In this study, a weight penalty is adjusted to modify the function L by applying a γ value to save the weights values:

$$L = \sum_{j=1}^{N} \sum_{i=1}^{M} -d_j^{(i)} \log z_j^{(i)} + \frac{1}{2} \sum_k \sum_L W_{k,l}^2 \tag{4}$$

where, W_k defines the connection between weights, k in layer l and L and K denotes the overall number of layers and the layer l connections, respectively.

One of the disadvantages of the CNN is that most of the layouts have been experimentally configured. Recently, the application of metaheuristics for resolving this problem have been increased [32, 33].

3. MODIFIED SEARCH AND RESCUE (SAR) OPTIMIZER

The key concept in optimization is to look forward of the best viable solution with its constraints and other problem specifications for a given problem [34, 35]. For a single problem, there may be numerous solutions that can be compared to selecting the best of them based on a pre-determined function called the objective (cost) function [36, 37]. Some sorts of the optimizer are metaheuristics, which are inspired by nature, human societies, and physics to find solution for numerous kinds of problems [38].

In coincidence with other algorithms, optimization algorithms are commonly used to obtain the optimum solution or avoid from the optimal local solution [39]. In recent years, one of the most promising studies was in the area of seeking a solution based on design, which is analogous to social or natural systems [40]. Their implementation is with continuous innovative-base methods that have very good achievements to solve problems of the complication class (NP-Hard).

Of late, some kinds of metaheuristics are defined that are with different phenomena-base. For example, Shark Smell Optimizer [41], world cup optimizer[42], artificial bee colony optimizer[43], etc.

3.1. Basic Search and Rescue (SAR) Optimizer

One of the newest techniques for solving the optimization problems is the Search and Rescue (SAR) optimizer. The SAR is a technique to obtain the optimum solutions for optimization problems. The SAR algorithm is inspired by the individuals that are searching for the lost persons. Due to this searching, the individuals who find more clues, have higher chance to find the lost person and indicate better position. In this algorithm, the cost value is the value of the location that individuals are in it for searching and the solution is the location of the individuals [44]. If the position found is not sufficiently suitable, the individuals search for better positions. By considering a memory matrix (M) to store the clues and also a location matrix (X) to store the position of the people with the same size of M., the initial population matrix will be obtained as follows:

$$M=\begin{bmatrix}X\\M\end{bmatrix}=\begin{bmatrix}X_{1,1} & \cdots & X_{1,d}\\ \vdots & \ddots & \vdots\\ X_{n,1} & \cdots & X_{n,d}\\ M_{1,1} & \cdots & M_{1,d}\\ \vdots & \ddots & \vdots\\ M_{n,1} & \cdots & M_{n,d}\end{bmatrix} \quad (5)$$

where, n and d are the candidate quantities and the problem dimension, respectively.

The search direction updating is given below:

$$u_i=(X_i-C_k), \quad (6)$$

where, k ($k \neq i$) describes a random value between 1 and $2N$, and X_i and C_k are the position of the human number i and the clue number k, respectively. It should be noted that because if $i=k$, X_i will be equal to C_i, so, $k \neq i$.

For avoiding of searching the duplicate positions, the X_i dimensions changing is not satisfactory by moving in the position of Eq. (6). Here, a binomial crossover operator is used to apply on the constraints. In the event that the expected clue is better than the present clue, an area will be searched for the clue and the u_i direction. Else, the searching position in u_i has been continued. Consequently, the updated position of the dimension number j for the human number i is as follows:

$$X'_{i,j}=\begin{cases}\begin{cases}c_{k,j}+r_1\times(X_{i,j}-C_{k,j}) & if\ f(C_k)>f(X_i)\\ X_{i,j}+r_1\times(X_{i,j}-C_{k,j}) & otherwise\end{cases}\\ if\ r_2<se\ or\ j=j_r, j=1,\ldots,d\\ X_i\quad otherwise\end{cases} \quad (7)$$

where, se describes a parameter between 0 and 1, $c_{k,j}$ determines the location for the dimension number j and the clue number k, j_r is a random value between 1 and d, $f(X_i)$ and $f(C_k)$ denote the cost amounts of the solutions C_k and X_i, respectively, and r_1 and r_2 represent two random values in the ranges $[-1,1]$ and $[0,1]$, respectively.

Afterward, for giving a local optimization for the algorithm, the current position of the humans should be considered. To do so, different connection of the clues from the previous stage are utilized. The position has been updated by the individual number i as follows:

$$X'_i=X_i+r_3\times(C_k-C_m), \quad (8)$$

where, r_3 signifies a random amount in the range [0, 1], and k and m signify two random values in the range $[1,2N]$, i.e. $i\neq k\neq m$.

The candidate should be checked to be in the solution space. If the candidate has a value outer than the search space, the following equation will be performed:

$$X'_{i,j}=\begin{cases}\dfrac{(X_{i,j}+X_j^{max})}{2} & if\ X'_{i,j}>X_j^{max}\\ \dfrac{(X_{i,j}+X_j^{min})}{2} & if\ X'_{i,j}<X_j^{min}\end{cases} \quad (9)$$

where, X_j^{min} and X_j^{max} denotes the minimum and the maximum threshold amounts for the j^{th} dimension, respectively.

In this step, if $X'_i(f(X'_i))>(f(X_i))$, the previous position (X_i) would be stored in a random array in

M as a new position.in otherwise, the position will be ignored and the memory will not be renewed, that is:

$$M_n = \begin{cases} X_i \ \ if \ \ f\left(X_i^{'}\right) > f\left(X_i\right) \\ M_n \ \ otherwise \end{cases} \tag{10}$$

$$X_i = \begin{cases} X_i^{'} \ \ if \ \ f\left(X_i^{'}\right) > f\left(X_i\right) \\ X_i \ \ otherwise \end{cases} \tag{11}$$

where, M_n signifies the position for clue number n in memory matrix, and n describes a random number in the range [1, N].

Another important term in the algorithm which is considered is time. This term has been modeled such that if each onlooker couldn't find a proper clue in a sure time, it should left the position to a new direction. This can be written as follows:

$$usn_i = \begin{cases} usn_i + 1 \ \ if \ \ f\left(X_i^{'}\right) < f\left(X_i\right) \\ 0 \ \ otherwise \end{cases} \tag{12}$$

where, usn represents the unproductive search number.

In the event that $usn > MU$, the person has been moved into another position over the search space. So, with a random solution, the current solution is replaced in the search space based on Eq. (11) for a possible solution if $usn > MU$.

Also, for an impossible solution, if $usn > MU$, the memory matrix with the lowest degree of will be chosen and the present candidate will be replaced with this solution and the present solution substitute the memory matrix, i.e.

$$X_{i,j} = X_j^{min} + r_4 \times \left(X_j^{max} - X_j^{min}\right) \\ j = 1, 2, \mathrm{I}, d \tag{13}$$

where, r_4 signifies a random amount between 0 and 1.

3.2. *Modified search and rescue (MSAR) optimizer*

Despite, search and rescue (SAR) optimizer has several advantages in finding the best global solution, it has also some disadvantages that should be resolved [45-48]. The main shortcoming of this algorithm is its shortcoming in easy falling into the local optimum. Several modifications have been introduced to refine the exploration of the metaheuristics. In this study, we use Chaotic map. The main advantage of the chaos-based SAR algorithm toward its basic mode is that is able to avoid from sticking in the local optima points following by upper velocity in the convergence. In the considered MSAR optimizer, the variable x_{Rand} has been modeled by the sinusoidal chaotic map as follows:

$$X_{rand,k} = ap_k^2 \sin\left(\pi p_k\right) \\ p_0 \in [0,1], a \in (0,4] \tag{14}$$

where, k signifies the iterations' number.

This improvement makes the searching model easy for updating.

Also, in the algorithm, for giving a good equivalence between local and global optimization, the Gaussian mutation mechanism has been utilized [49]. For the Gaussian distribution, the Probability Density Function (PDF) is achieved as follows:

$$g(x) = \frac{1}{\sqrt{2\pi\sigma}} \exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right) \tag{15}$$

where, σ^2 describes the variance of the Gaussian PDF, μ signifies the Gaussian distribution expectation. This variation is performed to candidate position updating of the SAR algorithm as follows:

$$X_{i,j}^{'\,(DSAR)} = X_{i,j}^{'} \times \left(1 + k \times g(0,1)\right) \tag{16}$$

where, k denotes a decreasing random amount between 0 and 1, and $g(0,1)$ signifies the standard Gaussian distribution. Here, $X_{i,j}^{'\,(DSAR)}$ defines the new updating mechanism, and $X_{i,j}^{'}$ defines all of the three update formulations in original SAR, i.e. Eq. (7), Eq. (9), and Eq. (13).

3.3. *The verification phase*

To give a proper validation for the proposed MSAR algorithm, it has been verified based on applying to some renown standard benchmark functions including Ackley, Rastrigin, Sphere, and Rosenbrock and a comparison of its results with some latest metaheuristic algorithms including Spotted Hyena Optimizer (SHO) [50], Multi-Verse Optimizer (MVO) [51], Locust Swarm Optimizer (LSO) [52], Manta Ray Foraging Optimizer (MRFO) [53], and the basic search and rescue

(SAR) optimization algorithm [11] were carried out. Table 2 states the employed benchmark functions for validation.

Table 3 indicates the parameter amounts of the studied algorithms.

The simulations have been performed to Laptop with configuration: Core i7-4720HQ 1.60 GHz with 16 GB RAM, based on the MATLAB 2017b environment.

Four measurement indicators are used for analyzing the results, including the lowest value (Min), the highest value (Max), the average value (Mean), and the standard deviation (std) of all of the benchmark functions based on the studied algorithms.

As can be observed from Table 4, the proposed MSAR algorithm offers the best (minimum) value for all of the studied benchmark functions that indicates the algorithm with better accuracy toward the other analyzed algorithms. In the analysis, the minimum value for standard deviation of the proposed MSAR algorithm shows its higher consistency toward different runs.

3.4. Hybrid CNN/MSAR

In this study, a different policy has been utilized for defining the number of hyper-parameters in CNN so that in addition to assuming the most suitable hyper-parameters of the CNN, it can consider each moment of running.

As beforementioned, the main idea is to plan an optimized model using CNN model for iron ore price volatility forecasting. The idea is to adjust an optimized procedure for advancing the system precision. The candidate solutions includes a series of integers. The minimum acceptable value for max pooling is set 2 such that there is no lower size, and the maximum limitation is the sliding window size. Another consideration is that the sliding window has lower value toward the input data. At that time, a collection of solutions were randomly generated and then, the solutions have been measured. So, the half-value precision of the network has been assumed as the objective function on a data forecasting verification process. The universal policy requires high computational costs due to the fact that the CNN population members need

Table 2. The employed benchmark functions for validation

Function	Equation	Constraint
Rastrigin	$f_1(x) = 10D + \sum_{i=1}^{D}\left(x_i^2 - 10\cos(2\pi x_i)\right)$	$[30,50]^D$
Rosenbrock	$\mathrm{f}_2(\mathrm{x}) = \sum_{\mathrm{i}=1}^{\mathrm{D}-1}\left(100\left(\mathrm{x}_\mathrm{i}^2 - \mathrm{x}_{\mathrm{i}+1}\right) + (\mathrm{x}_\mathrm{i} - 1)^2\right)$	$[-2.045, 2.045\,]^D$
Ackley	$\mathrm{f}_3(\mathrm{x}) = -20\exp\left(-0.2\sqrt{\frac{1}{\mathrm{D}}\sum_{\mathrm{i}=1}^{\mathrm{D}}(\mathrm{x}_\mathrm{i}^2)}\right) - \exp\left(\frac{1}{\mathrm{D}}\sum_{\mathrm{i}=1}^{\mathrm{D}}(\cos(2\pi \mathrm{x}_\mathrm{i}))\right) + 20 + \mathrm{e}$	$[-10,10]^D$
Sphere	$\mathrm{f}_4(\mathrm{x}) = \sum_{\mathrm{i}=1}^{\mathrm{D}}\mathrm{x}_\mathrm{i}^2$	$[-512,512]^D$

Table 3. The parameter values of the studied algorithms

Algorithm	Variable	Value	Algorithm	Variable	Value
MVO [51]	Traveling distance rate	[0.6, 1]	MRFO [53]	r	0
	Wormhole existence prob.	[0.2, 1]		γ	0.7
SHO [50]	$\vec{h}$	[5, 0]	LSO [52]	F	
	$\vec{M}$	[0.5, 1]		L	
SAR [44]	se	0.5		G	
	MU	20			

Table 4. The comparison achievements of the studied algorithms applied to the benchmark functions

Algorithm		f_1	f_2	f_3	f_4
LSO [52]	Min	10.7609	2.9587	1.5690	2.2903
	Max	3.9614e+3	1.7639e+2	1.0903e+5	4.6590
	Mean	2.5677e+3	3.2297e+2	1.5669e+4	3.6880
	std	2.5680e+4	1.9703e+2	2.5568e+4	4.5600
SHO [50]	Min	8.1415	2.1216	1.5192-3	1.3469
	Max	348.1297	1.3124	3.5158e-2	3.2255
	Mean	85.3127	1.1593	2.2017e-2	2.5369
	std	64.1695	1.2455	1.3146e-2	3.2243
MVO [51]	Min	6.0015	1.4292e-5	2.7515e-5	1.2259
	Max	3.1609e+2	0.1187	0.1255	2.1242
	Mean	67.2966	0.1218	0.1138	1.2260
	std	219.2007	1.2072	3.5588e-5	3.0422
MRFO [53]	Min	1.1137	8.6197e-18	3.6248e-8	0.1269
	Max	13.1216	1.3928e-16	2.0452-7	2.0457
	Mean	10.1716	1.1844e-16	2.1513-7	1.5851
	std	5.1646	1.1363e-16	3.0458e-8	0.1498
SAR [44]	Min	1.0239	7.1275e-21	5.8316e-11	5.1146e-10
	Max	12.0939	7.2858e-19	3.2542e-10	7.1254e-9
	Mean	7.4300	19.2472e-19	1.3938-10	1.2853e-9
	std	3.5572	1.1425e-19	5.1215e-11	1.2245e-10
MSAR	Min	0.0213	3.3453e-22	1.0294e-11	5.0479e-15
	Max	2.2514	1.0175e-21	1.3786e-10	1.5223e-14

to be trained for 1300 iterations on the forecasting dataset based on the backpropagation algorithm.

The suggested method is then validated on the considered data variables. This study employs biases and weights for optimization, that is:

$$W = \left[w_1, w_2, \ldots, w_p \right] \quad (17)$$

$$A = \left[a_1, a_2, \ldots, a_A \right] \quad (18)$$

$$w_n = \left[w_{1n}, w_{2n}, \ldots, w_{Ln} \right] \quad (19)$$

$$b_n = \left[b_{1n}, b_{2n}, \ldots, b_{Ln} \right] \; l = 1, 2, \ldots, L \;\; n = 1, 2, \ldots, A \quad (20)$$

where, n signifies the candidates' values, l defines the layer index, w_{in} indicates the value of the weight in layer i, and A and L represent the overall number of candidates and the total number of layers, respectively. Consequently, the variables for optimization are as below:

$$W_n = [W, A] \quad (21)$$

The achieved error between the system output and the reference is obtained as follows:

$$E = \frac{1}{T} \sum_{i=1}^{T} \sum_{j=1}^{k} (d_{ji} - o_{ji})^2 \quad (22)$$

where, k represents the output layers' number, T determines the number of training samples, and d_{ji} and o_{ji} describe the desired and the output amount of the CNN, respectively.

Another benefit of utilizing the BP method is that doesn't need the backward stage as a complex procedure. Fig. (2) depicts the method of applying MSAR to the CNN.

4. PROBLEM FORMULATION

The present study uses a combined model using an optimized convolutional neural network based on a developed version of the search and rescue (SAR) Algorithm (MSAR-CNN). The mentioned model is then used for iron ore price volatility forecasting. By choosing N numbers of initial

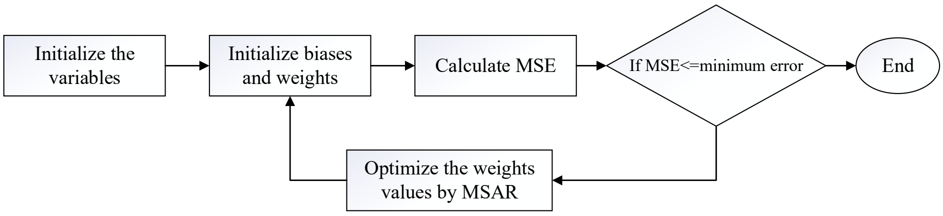


Fig. 2. Optimizing the CNN based on suggested MSAR

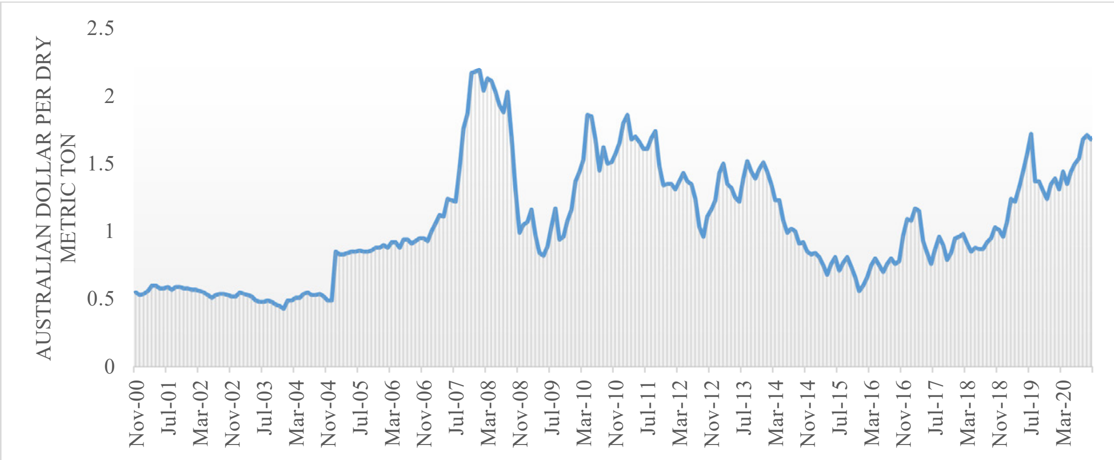


Fig. 3. Iron Ore Monthly Price/Australian Dollar per Dry Metric Ton

solutions, the MSAR-NN starts. The solutions include biases and weights for the network. For validating of the proposed tool, the Root Mean Square Error (RMSE) between the main data and the forecasted value has been achieved, i.e.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(y_i - \widehat{y}_i\right)} \tag{23}$$

where, y_i, and $\widehat{y}_i$ describe the original and the forecasted values, respectively.

As can be seen from Eq. (23), the solution with minimum $RMSE$ value specifies the best solution for the problem and the other candidates should be change their direction based on it and using updating process. This process will be continued until the stopping criteria has been reached.

5. DATA DESCRIPTION

The data analyzed here is extracted from [54]. The data contains 240 Iron Ore Monthly Price observations of the Australian dollar per Dry Metric Ton from November 2000 to Oct 2020. For validation, the first 90% (from Nov 2000 to Oct 2018) of data have been employed for training and the remained 10 % (from Oct 2018 to Oct 2020) have been employed for testing. Fig. (3) shows the Iron Ore Monthly Price/Australian Dollar per Dry Metric Ton [54].

For obtaining a more precise result, The forecasting model has been applied to a collection of forecasting variables with a notable connection with iron ore prices. In particular, various financial indexes with multiple domains and scales are included in the selected forecasting variables, so homogeneous dataset can be achieved by a data normalization. By considering the variables as X_i, their normalized value (X_i^{norm}) can be obtained by the following:

$$X_i^{\text{norm}} = \frac{X_i - \underline{X}}{\overline{X} - \underline{X}} \tag{24}$$

where, $i = 1, 2, \ldots, 240$ and $\underline{X}$ and $\overline{X}$ describe the lowest and highest values of the basic data, respectively.

Generally, the suitable selection of the input parameters is significant in forecasting model. In this study, for increasing the accuracy, 10 different variables are provided including: Australian Dollar exchange AUD. Based on the findings by [55], the commodity-exporting exchange rates for predicting the commodity costs.

The monthly Australian Dollar exchange is selected as variable, because this country is the largest exporters of the iron ore globally. Another variable is the Japan exchange rate which has a low capability of iron ore production, but is the second largest importer of it.

The inflation rate is another important input variable utilized in this analysis. This is a major macroeconomic factor affecting the market for commodities. Since the United States and the PRC are the world's first and second largest economies, the inflation rates of them are used as forecast variables. The energy sources derived by the oil and the prices of different metals has also important influence on the iron ore forecasting [56]. This makes us to use this variable as another case of the forecasting. Totally, the utilized variables that are extracted from November 2000 to Oct 2020 are as follows: the observation data of RMB and AUD exchange rates [57] in a month, the inflation rates of China and the USA [58], oil [59], silver [60], copper [61], gold [62], and scrap prices [63].

6. RESULTS AND DISCUSSIONS

6.1. Measurement indicators

Three measurement metrics have been applied to analyze the efficacy of the prediction techniques, including Mean Absolute Error (MAE), Mean Square Error (MSE), Relative Standard Deviation (RSD), RMSE, and Average Absolute Relative Deviation (AARD). The study is intended to assess the consistency and efficacy of the proposed model. The formulations for these measures are given as follows:

$$\mathrm{MAE} = \frac{1}{N} \times \sum_{t=1}^{N} \left| z_i - \hat{z}_i \right|^2 \tag{25}$$

$$\mathrm{MSE} = \frac{1}{N} \times \sum_{t=1}^{N} \left(z_i - \hat{z}_i \right)^2 \tag{26}$$

$$RSD = \sigma / \mu \tag{27}$$

$$RMSE = \sqrt{\frac{1}{N} \times \sum_{t=1}^{N} \left(z_i - \hat{z}_i \right)^2} \tag{28}$$

$$\mathrm{AARD} = \frac{100}{N} \times \sum_{t=1}^{N} \left| \frac{z_i - \hat{z}_i}{z_i} \right| \tag{29}$$

where, μ and σ describe the mean and the standard deviation values, respectively.

6.2. Simulations

For volatility forecasting in the iron ore price, the simulations were applied to approve the high efficiency of the forecasting variables.

Some validations were performed to test the efficiency of the suggested model. Some well-known approaches, including simple neural network [17], PSO-based [64], Intelligent Integrated Optimizer (IIO) [65], Genetic Neural Network (GNN) [66] are also compared with the same data sets for proper validation. For validation in this paper, as previously mentioned, MSE, RMSE, MAE, and AARD are employed.

The constraint of biases and weights are between -1 and 1 and the population size of the algorithm are considered for neural networks, and their iterations are considered to be 100 and 200, respectively, with 40 independent runs. Table 5 shows that a satisfactory fitting of the data based on various measurement indicators is given by the proposed model.

For more clarification of the importance of the suggested MSAR-ANN model, a comparison with aforementioned latest techniques based on two different data splitting of training and testing data were carried out: the first is splatted as 60 by 40, and the second is splitted by 90 by 10 for training and testing data, respectively (see Table 6).

From the results of Table 6, the presented MSAR-ANN has a high superiority toward the other compared methods in both experiments. Also, the results show that the more training data,

Fig. 5. The comparative performances analysis of the studied methods for the test set

Models	Applying the ratio of 60 by 40				Applying the ratio of 90 by 10			
	MSE	RMSE	MAE	AARD	MSE	RMSE	MAE	AARD
ANN [17]	0.0348	0.1709	0.1471	70.72	0.0182	0.1200	0.1048	43.4755
PSO-based [64]	0.0270	0.1518	0.1179	35.27	0.0152	0.1104	0.0875	36.9978
IIO [65]	0.0210	0.1354	0.1083	32.51	0.0123	0.0988	0.0787	33.3714
GNN [66]	0.0230	0.1406	0.1119	33.85	0.0119	0.0962	0.0764	32.2648
MSAR-ANN	0.0149	0.1153	0.1025	32.04	0.0084	0.0812	0.0658	27.5937

Table 6. The performance analysis of the comparative methods by different training and testing divisions

Models	Applying the ratio of 60 by 40			Applying the ratio of 90 by 10		
	RMSE	MSE	MAE	RMSE	MSE	MAE
ANN [17]	30.70%	56.82%	42.63%	47.64%	96.54%	61.58%
IIO [65]	13.91%	30.75%	4.57%	20.57%	58.54%	20.95%
PSO-based [64]	22.67%	46.39%	13.75%	34.38%	78.95%	34.93%
MSAR-ANN	12.84%	27.73%	8.40%	16.40%	51.79%	16.85%

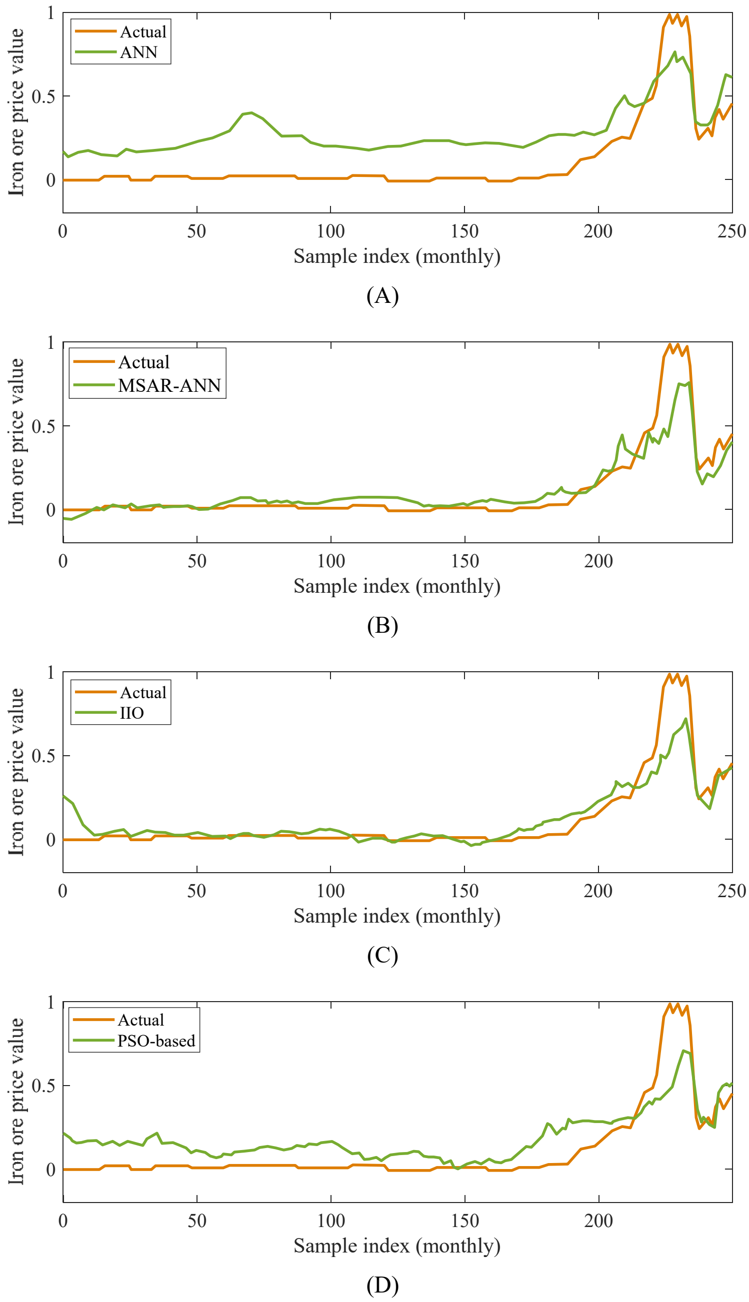


Fig. 4. The iron ore price forecasting method based on simple ANN, MSAR-ANN, GNN, IIO, and PSO-based method during the network training

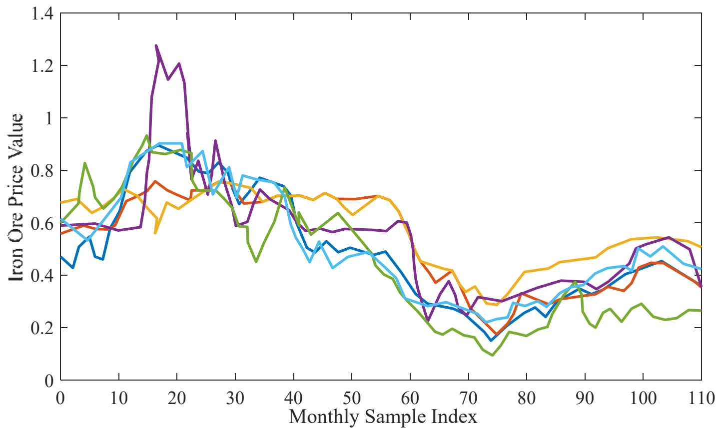


Fig. 5. The comparative performances analysis of the studied methods for the test set

Table 7. The performance for out of sample among the compared models

Models	Using the ratio of 70:30				Using the ratio of 90:10			
	MSE	RMSE	MAE	AARD	MSE	RMSE	MAE	AARD
MSAR-ANN	0.0139	0.1154	0.1025	31.24	0.0074	0.0812	0.0648	27.69
KNN [67]	0.0281	0.1663	0.1116	79.44	0.0232	0.1507	0.0910	71.38
SVR [68]	0.0257	0.1588	0.1051	76.32	0.0119	0.1062	0.0768	50.36
NLANN [17]	0.0205	0.1412	0.1077	71.84	0.0136	0.1140	0.0799	59.22

Table 8. The comparison results of the of the proposed method than the compared methods.

Authors(s)	Model	Data type	Commodity	Split ratio		Performance measure		
				Training	test	RMSE	MSE	MAE
Dehghani and Bogdanovic [69]	Bat algorithm	Monthly	Copper	90	10	0.153	-	-
Ravi et al. [70]	GA– ANFIS	Monthly	Copper	85	15	0.0834	0.0088	0.0665
Ewees et al. [22]	PVN-BP	Monthly	Copper	95	5	0.13827	-	-
Zhou et al. [71]	BIC-GA-RELM	Daily	Iron	85	15	2.0023	4.0025	1.836
Li et al. [72]	VMD-GASVM 2	Monthly	Oil	80	20	0.559	-	-
Weng et al. [73]	Chaos þ MLP þ NSGA-II	Daily	Gold	90	10	-	0.01364	-
Proposed model	CGOA-NN	Monthly	Iron	95	5	0.0812	0.0084	0.0648

the more accuracy it will be.

In the suggested model, a number of notable contributions are obviously presented to enhance the precision of the prediction procedure. Fig. (4) shows that the MSAR-ANN-based iron ore price forecasting model has the highest efficiency with respect to comparative methods. Likewise, the performance analysis of the comparative algorithms applied to the test set as shown in Figure.

To give more validation for the proposed method, a comparison of the proposed MSAR-ANN with some other latest and popular techniques including k-nearest neighborhood (kNN) [67], non-linear autoregressive neural network (NLANN) [17], and Support Vector Regression (SVR) [68] was performed. To indicate some out of sample competences among the comparative models, see Table 7.

Based on the results, the proposed MSAR-ANN obtains the optimum achievements during the analysis. Finally, Table 8 specifies the results of the MSAR-ANN compared with the other methods which have different data splitting for training and testing.

7. CONCLUSIONS

Iron ore is the major raw material for steel producing. The iron ore market was always influenced by various and changing conditions. In this industry, large and small producers, constant and seasonal exporters and consequently various actors are active. Upstream and downstream market analysis in the steel industry has always been considered and activists in this sector monitor not only the price of products, but also the price of raw materials such as iron ore. It is especially important to study the extent to which the decrease or increment in the cost of iron ore affects the demand and prices of other commodities. This leads researchers to work on designing a precise forecasting tool to give a good track to the decision makers.

Because of the nonlinear behavior and high complexity of the variables in the iron ore, artificial intelligence is the best choice of solution. This paper presented a new developed version of Convolutional Neural Network (CNN) for the forecasting. For achieving a more accurate results based on CNN, a modified version of the Search and Rescue (MSAR) optimization algorithm was designed and performed to it for increasing its performance in finding the iron ore price volatilities forecasting. For validating the algorithm, ten input variables including the inflation rates of US and Japan, the exchange rates of the Japanese Yen (JPY) and the Australian Dollar (AUD), and costs of oil, gold, copper, scrap, and silver and past iron ore costs were utilized. To indicate the efficacy of the suggested technique, its results by the analyzed parameters are validated by some indicator measurements such as relative standard deviation (RSD), Mean Absolute Error (MAE), Mean Square Error (MSE), Root Mean Square Error (RMSE), and Average Absolute Relative Deviation (AARD) and a comparison of its results with different well-organized techniques such as basic neural network, PSO-based, Intelligent Integrated Optimizer, Genetic Neural Network (GNN) using the same data sets were carried out. The results showed the superiority of the proposed technique than the compared techniques.

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