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Predicting Peak Particle Velocity Induced by Mining Blasting Using Optimized Deep Learning with Coronavirus Herd Immunity Algorithm

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Abstract

One of the most important economic sectors is mining. Open-pit mines are the most common form, and blasting is the most efficient method. This method can cause significant damage due to vibrations. Thus, monitoring and controlling vibrations is important. This research aims to predict vibrations based on the distance and quantity of explosives. To study this, vibrations were estimated using Peak Particle Velocity from seismograph devices. Measurements were done in two large Iranian mines, providing approximately 1000 data points. Considering the data complexity, a deep learning method was selected for modelling. Deep learning has numerous hyperparameters, and their correct adjustment impacts efficiency. The Coronavirus Herd Immunity Optimizer (CHIO) was used to find optimal values. Various criteria were used to test the model efficiency. The results indicate the optimization method improved predictions by at least 4%. The coefficient of determination for random forest, basic deep learning, and optimized methods was 0.861, 0.932, and 0.972. The root means square error values are 3.687, 2.338, and 1.146. The absolute mean percentage error indices are 0.169, 0.128, and 0.068. It is concluded that deep learning has acceptable performance. Its efficiency can be increased by optimization algorithms. The results show an excellent response to the integration of the CHIO method, demonstrating its good capability.

Keywords:
blasting, peak particle velocity, deep learning, herd immunity, coronavirus

1. Introduction

The increasing need of modern societies for diverse products has increased the dependence of manufacturing factories on the extraction of minerals, as the initial unit of the production chain. Open-pit mines are considered the largest supplier of mineral raw materials to production units. In these mines, minerals are extracted through drilling and blasting. Although this method leads to high-speed and large-scale production, it has significant drawbacks. This method generates significant vibrations that cause serious damage to buildings around the mine. These damages can be observed in the form of cracks or destruction of the building. Therefore, it is significantly important to control and manage these types of damage. To manage them, it is necessary to implement measures that are preceded by awareness of the magnitude of the vibration and its radius of effect. Considering the importance of the subject, this research attempted to record and collect data on the distance from the blasting site, the amount of explosive used for the blasting, and the corresponding vibration intensity generated in terms of Peak particle velocity in two large open-pit mines, resulting in a powerful tool for predicting the seismic situation of each blasting. Given the critical importance of controlling blasting vibrations, many researchers are dedicated to this field. A review of the work done in this field is provided as follows.

Armaghani et al. (2014) research developed a hybrid PSO-ANN model, which integrates Particle Swarm Optimization with an Artificial Neural Network, to provide simultaneous and accurate predictions for two critical blasting hazards: flyrock distance and ground vibration (PPV). The model was trained and validated using a robust dataset of 62 blasting events from a granite quarry, incorporating key design parameters such as burden, spacing, and powder factor. It demonstrated superior predictive performance, achieving notably high coefficients of determination of $R^2 = 0.957$ for flyrock and $R^2 = 0.988$ for PPV on the test dataset. A subsequent sensitivity analysis revealed that powder factor and stemming length were the dominant factors controlling flyrock, while maximum charge per delay was the paramount

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variable for ground vibration. These findings robustly establish the proposed PSO-ANN model as an effective and reliable expert system, offering a practical tool for engineers to preemptively assess risks and design safer, more environmentally controlled blasting operations. **Dindarloo (2015)** investigated and predicted the vibration caused by the blasting using a genetic algorithm. In this study, 9 input variables were used to predict the vibration frequency at different distances from the blasting face. The high coefficient of determination with the absolute mean percentage error indicated the suitability of the algorithm in predicting the amount of vibration. **Ghasemi (2016)** presented a new hybrid approach based on the combination of adaptive neuro-fuzzy inference system and particle swarm optimization to predict the Peak particle velocity during the blasting stage in open pit mines. The models were trained and tested based on real data from 120 blasting cases in the Sarcheshmeh copper mine. The results obtained from the comparison of the models showed that the adaptive neuro-fuzzy inference system and particle swarm optimization model provided better results compared to other models. **Saghatforoush et al. (2016)** developed a hybrid Artificial Neural Network (ANN) model, optimizing it with the Ant Colony Optimization (ACO) algorithm, to predict and mitigate two critical blasting hazards: flyrock distance and back-break in a granite quarry. By employing ACO to refine the ANN's initial weights and biases, they significantly enhanced its predictive accuracy beyond that of a conventional, standalone ANN. Their results demonstrate the hybrid model's superior performance. For flyrock prediction, it achieved a coefficient of determination (R^2) of 0.964, markedly outperforming the standard ANN (R^2 = 0.934). Similarly, for back-break prediction, the hybrid ANN–ACO model delivered greater accuracy, with an R^2 of 0.980 compared to 0.960 for the conventional model. Consequently, this optimized tool allows engineers to proactively adjust key blasting design parameters—including burden, spacing, hole depth, and powder factor—before operations commence. This capability directly supports the minimization of hazardous side effects, thereby enhancing both safety protocols and economic efficiency at the site. **Hasanipanah et al. (2017)** studied the ground vibration caused by blasting in the Bakhtiari Dam area using a genetic algorithm. In their study, they developed equations to predict ground vibration using the mentioned algorithm. The maximum payload weight at each delay and the distance between the monitoring site and the blasting point, as well as the most influential parameters on ground vibration, were used as inputs for modelling. The Peak particle velocity parameter, as an indicator for evaluating ground vibration caused by the blasting, was also considered as an output or dependent variable for modelling. They measured the Peak particle velocity parameters accurately by considering 85 blasting cases and then compared the results with several empirical prediction models. The results showed that the genetic algorithm is an acceptable model compared to empirical prediction models for predicting the Peak particle velocity, considering the mean sum of squared error and multiple determination coefficient indices. In their study, **Asl et al. (2018)** attempted to design appropriate parameters for blast pattern design including overburden, spacing, hole depth, stemming, specific charge, charge at each delay time, and earth strength index to reduce inappropriate crushing and rock fly using artificial neural network and firefly algorithm. After collecting data and selecting the most effective parameters for rock fly and crushing, they developed an artificial neural network model and used the firefly algorithm for the optimization process. The results of modelling and optimization showed 42.9% and 32.9% reductions in rock fly and crushing, respectively. **Nguyen et al. (2019a)** compared the ground vibration and Peak particle velocity caused by open-pit coal mine blasting using boosted generalized additive models, an empirical equation, a support vector machine, and an artificial neural network. They used several statistical indicators, such as coefficient of determination, mean sum of squared error, and mean absolute error to evaluate the quality of each prediction model. The results showed that the proposed model had the highest accuracy, and the height difference between the blasting site and the monitoring site was one of the dominant parameters governing the Peak particle velocity prediction models. In their other work in same year, **Nguyen et al. (2019b)**, presented a new prediction model based on the Gaussian process regression approach to estimate ground vibration caused by blasting. They examined 210 blasting in an open-pit mine in Ghana, of which 130 data points were used for developing model training. The remaining 80 data points were used to evaluate the performance of the Gaussian regression model. Then, they compared the formulated model with other standard prediction methods, such as the generalized regression neural network, the radial basis function neural network, and the recurrent neural network, and with four conventional ground vibration predictors. The results showed that the proposed Gaussian process regression approach can predict ground vibration with much greater accuracy than the standard methods. **Bui et al. (2019)** studied the effects of blasting in an open-pit mine in Vietnam. During this study, 25 blasting were examined. In their study, they achieved a new hybrid model for predicting ground vibration caused by blasting by combining fuzzy clustering models and pseudo-recurrent neural networks. The results of the studies show that the new hybrid model has higher accuracy compared to old models, such as artificial neural networks, forest, and pseudo-recurrent neural networks. The proposed model could be used to control the adverse effects of ground vibration caused by blasting. **Fang et al. (2019)** considered ground vibration caused by blasting as the main objective in their study and presented a new artificial intelligence system to predict ground vibration caused by blasting with high accuracy, which was based on the algorithm based on the five-rules and the imperialist competition algorithm, and they called it the imperialist competition hybrid method based on the five-rules. In the research, the imperialist competition algorithm was considered to optimize the “five-rules” concept. To evaluate the efficiency of the new hybrid method presented, they selected the “classical five-rules” and the support vector machine as benchmark methods. In addition, they used two empirical equations to develop models based on experimental data sets to predict ground vibration caused by blasting for comparison with the proposed new hybrid model. They also conducted their study on an open-pit mine in Vietnam using experimental models, support vector machines and extended random models based on 125 blasting cases. Then, evaluated the accuracy using the mean absolute error, the mean sum of squared error, and coefficients of determination. The research findings indicated that the proposed new hybrid model provides the highest accuracy compared to other methods. **Yang et al. (2020)** studied the prediction of ground vibration caused by blasting using hybrid artificial intelligence methods. Their study was based on optimized support vector regression with the firefly algorithm, genetic algorithm, and particle swarm optimization algorithm. In addition, they used spindle-face, artificial neural network-based models, and some well-known empirical models. During this research, they used 90 datasets collected from two open-pit mines. Their comparison results based on several statistical criteria indicated that the hybrid method has significantly higher efficiency than other hybrid models based on support vector machines. **Azimi et al. (2019)** proposed a new evolutionary artificial neural network that is optimized with a genetic algorithm for predicting Peak particle velocity. The proposed artificial neural network-based genetic algorithm is a hybrid method that provides a systematic and automated approach to find the appropriate ANN architecture, number of neurons, activation functions, training algorithm, and number of cycles. The dataset consisting of maximum load weight at each delay, horizontal distance, radial distance, and new modified radial distance between the monitoring station and the blasting station at the Songun copper mine site in Iran was used for the proposed validation.

The approach of comparing the performance of the proposed ANN-based genetic algorithm hybrid model with statistical indicators shows the superiority of the ANN-based genetic algorithm hybrid model over empirical predictors and the neuro-fuzzy inference system. Finally, the results indicate that the proposed ANN-based genetic algorithm hybrid method is effective in finding the optimal architecture of the ANN while predicting the Peak particle velocity. **Nguyen et al. (2020)** used an artificial neural network to predict air blasts caused by blasting in the open-pit coal mine of Diona, Vietnam. The parameters used in these models included charge per delay, overburden, spacing, stemming length, specific charge, air humidity, and monitoring the station distance. The results of the research showed that the multilayer neural network model has the most accurate prediction compared to previous models. **Al-Bakri et al. (2021)** confirmed the superiority of Artificial Neural Networks (ANNs) in predicting and optimizing blast-induced impacts such as vibrations and flyrock. Their findings show ANN models achieve greater accuracy and efficiency than traditional empirical approaches, making them critical for safety and environmental management in blasting projects.

Zhang et al. (2021a) investigated the effect of the Peak particle velocity caused by blasting in underground coal mines. This study discussed the relationship between the magnitude of mining events and the Peak particle velocity with the resulting stress increase, which is of important reference significance for studying the mechanism and early warning of rock bursting. **Zhang et al. (2021b)** predicted the Peak particle velocity caused by open-pit mining using an artificial intelligence-based method. In this paper, a combination of extreme machine learning and multiverse optimization methods is presented to predict the Peak particle velocity from 137 blasting events. As a result, better accuracy was achieved compared to traditional models. **Zeng et al. (2021b)** investigated and predicted the Peak particle velocity using hybrid machine learning. They concluded that a combination of boosting models can identify the most effective parameters affecting the Peak particle velocity values and predict them with high accuracy. **Hanifehnia et al. (2024)** focuses on predicting the distance of blast-induced flyrock, an undesirable environmental phenomenon in open-pit mines, using artificial intelligence methods and statistical techniques; they employ an _Artificial Neural Network (ANN-MLP)_ and a hybrid _ICA-ANN_ model (ANN optimized by the Imperialist Competitive Algorithm) to forecast flyrock distance considering parameters such as number of holes, hole spacing, burden, total charge, specific drilling, charge per hole and specific charge, and report that the ANN achieved RMSE = 9.31 m, MAE = 7.10 m, R2 = 0.81 while the ICA-ANN improved predictions to RMSE = 5.66 m, MAE = 4.60 m, R2 = 0.89; sensitivity analysis indicates explosive consumption and number of holes have the greatest impact. **Khosravimanesh et al. (2024)** noted that directly measuring the Rate of Penetration (ROP) in drilling is costly and time-consuming, making predictive models a valuable alternative. In their study, they evaluated linear, lasso, and ridge regression models on a dataset of 492 samples. Their comprehensive comparison, based on multiple error metrics, ultimately identified the Ridge regression model as the most reliable and accurate predictor for ROP.

Taiwo et al. (2024) presented new research about blasting process in a granite quarries. This study suc-

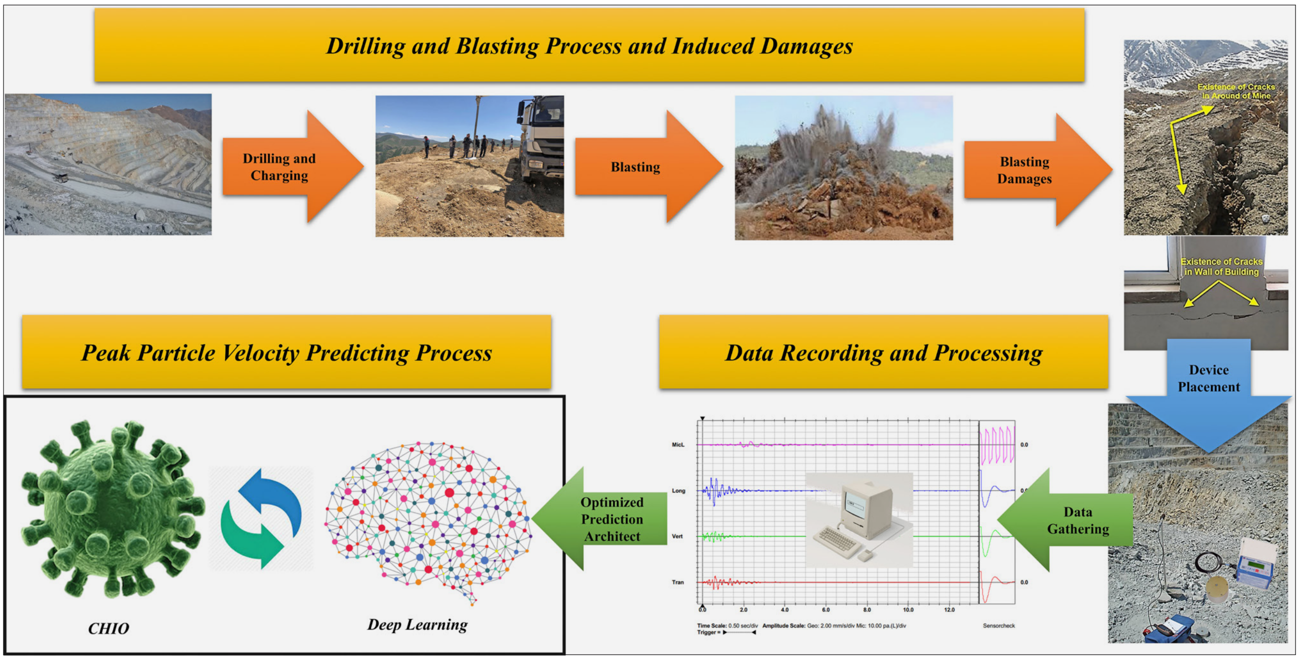


Figure 1. A schematic overview of the research stages

cessfully used an Artificial Neural Network (ANN) to predict profitability in Nigerian granite quarries, directly linking financial outcomes to blast design. By analyzing fragmentation data, it identified a 2m x 2m blast pattern as optimal and correlated higher blast efficiency with a better uniformity index. The research confirms the ANN model as a highly accurate profit forecasting tool, demonstrating the value of merging operational and financial data. **Taiwo et al. (2023)** in the other research, applied advanced ML models, including LSTM and SVR variants, to forecast flyrock in the Akoko Edo quarries. From their data, burden distance and charge amount were critical factors influencing projections. The LSTM model proved superior in accuracy, significantly outperforming other algorithms and providing a reliable tool for risk assessment. Further demonstrating the value of machine learning in mining, a study on the Dongri-Buzurg mine utilized a hybrid artificial neural network (ANN) to predict blast-induced Peak Particle Velocity (PPV). By integrating optimization techniques, the model improved prediction accuracy, which led to optimized blasting parameters and reported benefits in safety, environmental protection, and operational efficiency (**Bisoyi et al., 2025**). **Ebrahimabadi et al. (2025)** investigated the prediction of Roadheader performance, specifically the Instantaneous Cutting Rate (ICR), which is critical for optimizing excavation in tunneling and mining. To forecast ICR based on rock and machine parameters at the Tabas coal mine, they employed and evaluated three models: a Support Vector Machine (SVM), the Firefly Algorithm (FA), and the Bat Algorithm (BA). Their results demonstrated that all models performed satisfactorily, but the Bat Algorithm (BA) proved superior, achieving the highest coefficient of determination ($R^2 = 0.9421$) and the lowest error metrics, thereby offering the most precise and realistic predictions.

Considering the research conducted and the existing research gaps, in this present research work, an attempt was made to first create a suitable database including the distance and amount of explosives as input variables and the Peak particle velocity as an indicator of the amount of vibration as a dependent variable using a seismograph in two large-scale open-pit mines, Songun and Golgohar. Then, the deep learning method was used as a predictive tool. Given the number of hyperparameters in this method and the uncertainty of the random and trial-and-error selection, the predictive method was augmented by integrating a herd immunity-based optimization algorithm to obtain a reliable hybrid method. It is also worth noting that the adverse effect of vibrations on the lives of people working in mines or people living in areas near the mine shows the necessity of using such research. Accurate assessment of vibration intensity is critical for ensuring correct mining developing direction.

2. Methodology

The occurrence of blasting in open-pit mines for mineral extraction is essential and inevitable. With the occurrence of a blasting, vibrating waves move rapidly in all directions and, when they collide with buildings, transfer their kinetic energy to them, causing various damages to them. These damages are the source of many life and financial risks. These risks affect all buildings located in the range of motion of seismic waves. These buildings can include mining facilities or residential houses around mining areas. These vibrations, along with other negative effects caused by mining blasting, are considered one of the most important negative consequences. Therefore, studying and investigating this phenomenon and then controlling and managing it is very important. Considering this issue, a path was drawn and implemented in this research work to provide this important information. The research path for this work includes recording and collecting the desired study data, analyzing and pre-processing the collected data, creating a predictive model, and optimizing the final model. **Figure 1** shows the overall research process taken to achieve the research goal in this study.

2.1. Developing Database

Considering the nature of the research subject as well as the implementation of the study on two open-pit mining sites, access to real data is inevitable. For this purpose, data on blasting in the two open-pit mines of Sungun Ahar and Golgohar Sirjan were monitored and recorded (see **Figure 2**). At this stage, by planning and replacing the Instantel Minimate Plus seismometer at important locations, various data related to the blasting and its seismic results were recorded and collected during the blasting operation. More than 1000 observations were recorded. This data included various information about the conditions of the blast holes and the distance from the blast site. Since the study aimed to investigate the relationship between the distance between the seismometer location and the center of gravity of the blasting and the amount of explosive used with the Peak particle velocity as an indicator of the magnitude of vibration, only this part of the data was used. **Figure 3** shows a sample of the content captured for blasting event number 27.

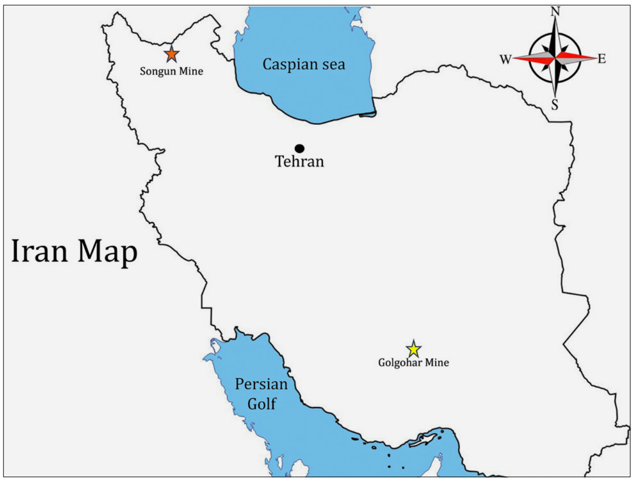
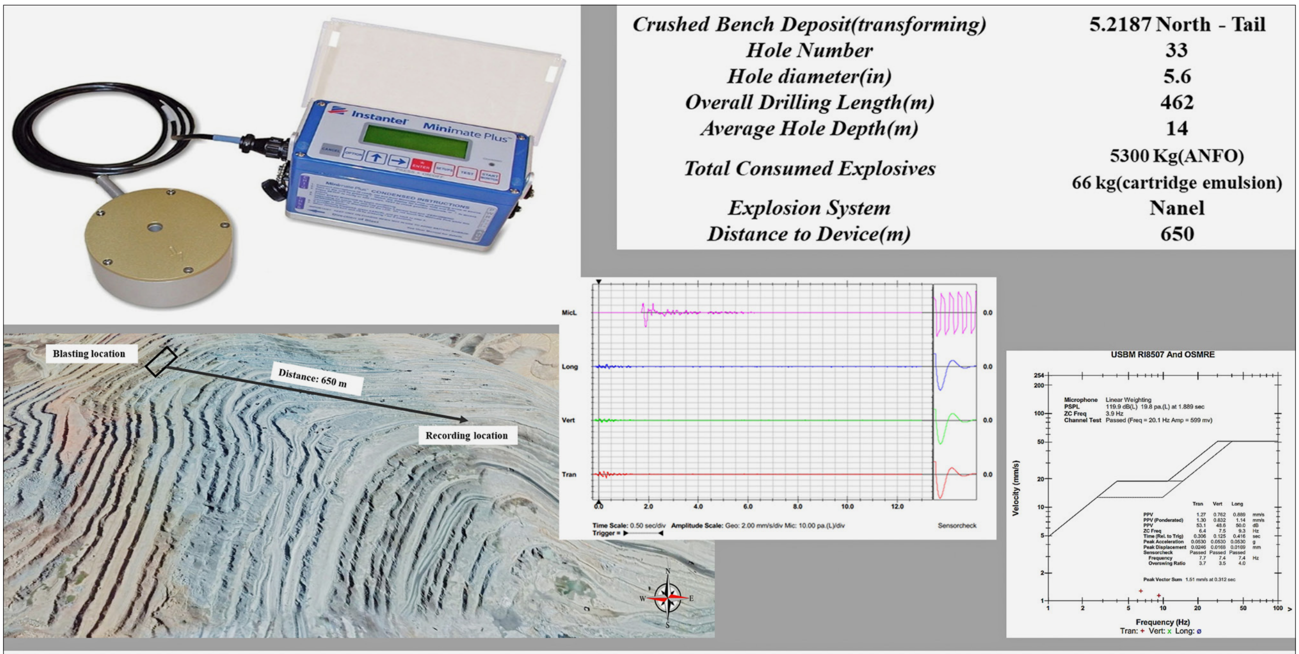


Figure 2. Location of the studied mines

2.2. Deep learning

Predictive modelling of diverse phenomena enables enhanced accuracy in operational planning. Artificial intelligence, which relies on its various tools, can provide acceptable predictions. Machine learning is one of the most important subsets of artificial intelligence-based methods offering a wide range of useful tools for prediction, including artificial neural networks. Among the subsets of neural network-based methods, deep learning techniques are considered to be one of the most efficient artificial intelligence tools. Deep learning refers to more complex and larger networks based on artificial neural networks. These networks differ from simple artificial neural networks in terms of characteristics. The frame-



Trigger	Tran Peak (mm/s)	Vert Peak (mm/s)	Long Peak (mm/s)	Mic Peak (dB)	PVS (mm/s)	Peak Acceleration(g)	Peak Displacement (mm)
Tran	1/27	0/762	0/889	119/9	1/51	0/0530	0/0246 Tran

Figure 3. An overview of the recorded data along with the location of blasting event number 27

work and architecture of these networks in deep learning give them high flexibility in dealing with complex problems and large volumes of data. Factors such as the type of network framework, the number of hidden layers, the number of neurons in each layer, activation functions, weight functions, optimization functions, and various other hyperparameters play an important role in defining and establishing a deep learning network.

The earth's condition, which involves facing a natural and self-made environment, does not allow any control and management over its key parameters. In conditions where there is no control over important environmental parameters, predicting behaviour is very difficult and complex. Therefore, facing and behaviour study of such environments for prediction requires the use of tools with high flexibility and power. On the other hand, as mentioned in the previous section regarding the nature of data, the number of data points collected is approximately 1000, which is a considerable number. Considering the above, the deep learning method was chosen to find the behavioural pattern between the input parameters, namely the distance from the blasting site and the amount of explosive, and the output parameter, namely the Peak particle velocity. Deep learning has various frameworks, among which the feedforward framework is the best option for working with tabular data. Other frameworks are used for working with time series data image data, etc. The architecture used for deep learning consists of an input layer containing two input parameters, followed by seven hidden layers, and finally, an output layer containing one output parameter. **Figure 4** shows the general scheme of the designed network architecture.

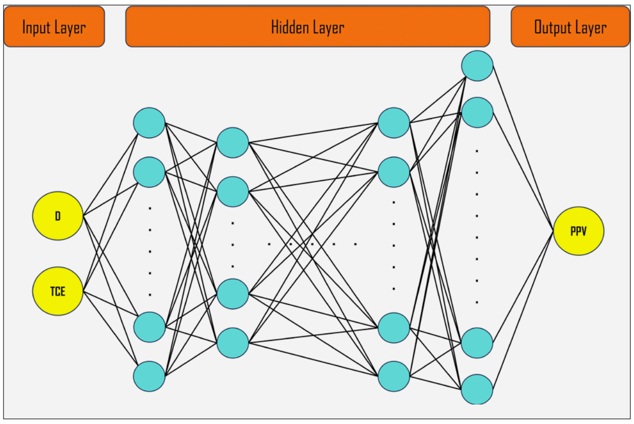


Figure 4. Overview of a deep learning network architecture

When applying deep learning methods, a portion of the data is designated as training data, while the remainder is reserved as test data. Typically, 70% of the data is allocated for training, and 30% is used for testing. This standard approach was adopted in this research.

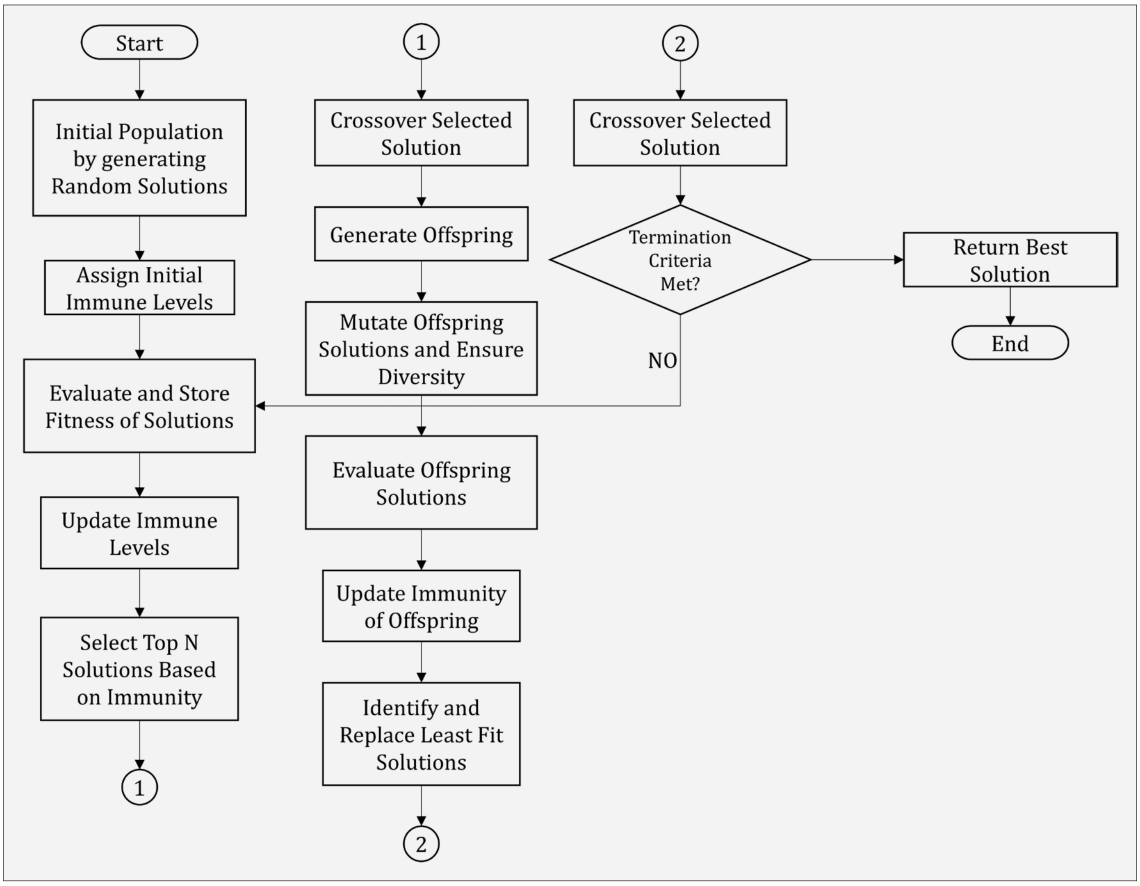


Figure 5. Flow chart of Corona Herd Immune Algorithm

2.3. Coronavirus Herd Immunity Optimizer (CHIO)

The coronavirus herd immunity optimizer, introduced by **Albetar et al. (2021)**, is a novel optimization algorithm based on human biological structure, classified under the subclass of nature-inspired optimization methods. This algorithm works on the coronavirus pandemic with the concept of herd immunity. The speed of the spread of the coronavirus infection depends on how directly infected individuals come into contact with other members of the community, which are modelled based on optimization concepts. The coronavirus herd immunity optimizer mimics the herd immunity strategy as well as social distancing concepts. This is a robust optimization algorithm that can solve optimization problems in a wide range of optimization domains. The different steps of the coronavirus herd immunity optimization process are given below. The flow chart of the coronavirus herd immunity optimizer algorithm is shown in **Figure 5**.

As can be seen from **Figure 5**, this algorithm, like other metaheuristic algorithms, creates a population of possible solutions by accepting the ranges of change of each input variable, and then by inserting them into the defined cost function, the best solution of that generation from the population is calculated and considered as the best solution up to that stage of the algorithm. Then, in the next stage, the second generation of the population of possible solutions is calculated based on the computational characteristics defined for this algorithm. After that, the cost function values are calculated again for each, and the best solution is selected and compared with the best solution of the entire process. In this way, the second iteration ends. The iterations of this algorithm continue until the defined stopping criterion is satisfied. For more information about this algorithm, refer to the source. For a more detailed explanation of optimization algorithm's calculation steps, different CHIO steps have been brought in following:

CHIO Algorithm Calculation Steps:

Initialization:

Initialize the population (individuals) with random solutions (HIS=15).

Define parameters:

Herd Immunity Rate (HIR=0.5)

Basic Reproduction Rate (BR=0.01)

Maximum Infected Cases Age (Max_age=3)

Fitness Evaluation

Evaluate fitness for each individual.

Virus Spread (Update Solutions)

For each individual, update its position based on infected cases:

If (rand ≤ BR), modify solution using:

$$X_i^{new} = X_i + r \cdot \left(X_i - X_j\right) \cdot I \quad (1)$$

Where:

X_i – current individual,

X_j – randomly selected infected neighbor,

r – random number,

I – binary infection indicator.

Herd Immunity (Crossover-like Update)

If (rand > BRR), update using herd immunity:

$$X_i^{new} = X_i + r \cdot (X_i - X_k) \cdot (1 - I) \quad (2)$$

Where X_k: a healthy (immune) individual.

Fitness Comparison & Replacement

Replace X_i with X_i^{new} only if the fitness is better.

Update Infection Rates

Adjust BR dynamically:

$$BR(t+1) = BR(t) \cdot \left(1 - \frac{t}{Max\_Iter}\right) \quad (3)$$

Termination

Repeat until Max_Iter (=1000) is reached or convergence is achieved.

The values enclosed in parentheses for each CHIO algorithm parameter and control parameter represent those utilized during the CHIO optimization process. These values were obtained through several trial-and-error attempts.

2.4. Date preprocessing

The first stage of the present research examines the data. To have acceptable results from predictive modelling, the quality of the input data is very crucial. The best models and algorithms cannot meet the lowest expectations when faced with poor-quality inputs. Therefore, monitoring and refining the data before importing them into the model is one of the most important steps in accessing a good model. This stage is called data pre-refining. The different stages of the preprocessing stage are presented in **Figure 6** below.

2.5. Optimization philosophy

Accessing the optimal value of the target variable has always been of interest in various engineering and non-engineering problems. The optimal value is a value that, for values other than that, the target function will provide more or less values. Consistent with the present study, the aim is to reach the most accurate tool for predicting the Peak particle velocity and, consequently, the target vibration level. The indicators that evaluate the accuracy and precision of the prediction methods in this study have been previously introduced. For example, considering the coefficient of determination index, the best performance of the prediction method occurs when this index has values close to one. In other words, one is the best value for the coefficient of determination. Therefore, the performance quality of the prediction method is the closeness of the coefficient of determination to the value of one. However, the target method in this study is a deep learning network. This method has various hyper-

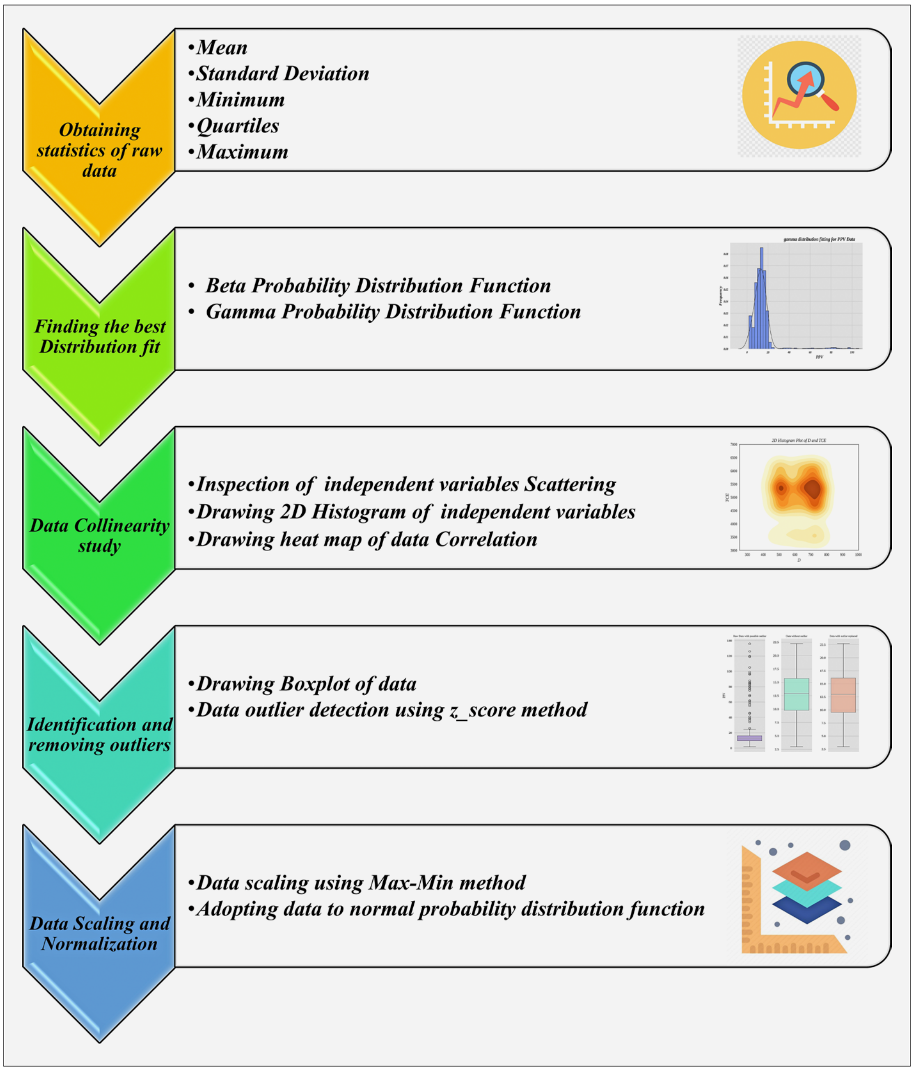


Figure 6. Various stages of data preprocessing to prepare it for entry into a deep learning model

parameters that affect its performance. The most important hyperparameters of this method include the number of hidden layers, the number of neurons in each layer, the types of functions involved in the layers, etc. The number of hyperparameters of a deep learning network is high. The values assigned to each of these hyperparameters have a direct impact on the performance quality of the deep learning network. **Figure 7** shows the effect of the number of neurons in the first hidden layer and the learning rate on the performance quality of the deep learning network by monitoring two indices: root mean square error and absolute percentage of average error. It is clear from all four figures that by changing the values of the two hyperparameters mentioned above, the change in the performance quality of the deep learning model is evident, indicating the high impact of the model behaviour on the values of the hyperparameters. Therefore, the selection of hyperparameter values is of considerable importance in discovering the optimal deep-learning network.

In the selection step of values for these hyperparameters, a random trial and error procedure can be used. This procedure provides the most accessible solution. Due to the lack of complete monitoring of the possible values, the space of each hyperparameter presents considerable uncertainty regarding the best performance of the deep learning network. On the other hand, due to the large number of hyperparameters, manual adjustment is very time-consuming. In another procedure, the best values are selected for the hyperparameters using optimization processes. In this method, by integrating prediction and optimization methods, a new hybrid method is created that provides the best results, considering the limitations of the optimization process.

2.6. Optimization process

As mentioned in the previous section on the necessity of the optimization process, the number of hyperparameters of a deep learning network is significant. Therefore, in this research work, the hyperparameters of the number of neurons in the hidden layers, the activation, the regulator and bias functions, and the learning rate were selected as the target hyperparameters for optimization. To create an optimized deep learning hybrid net-

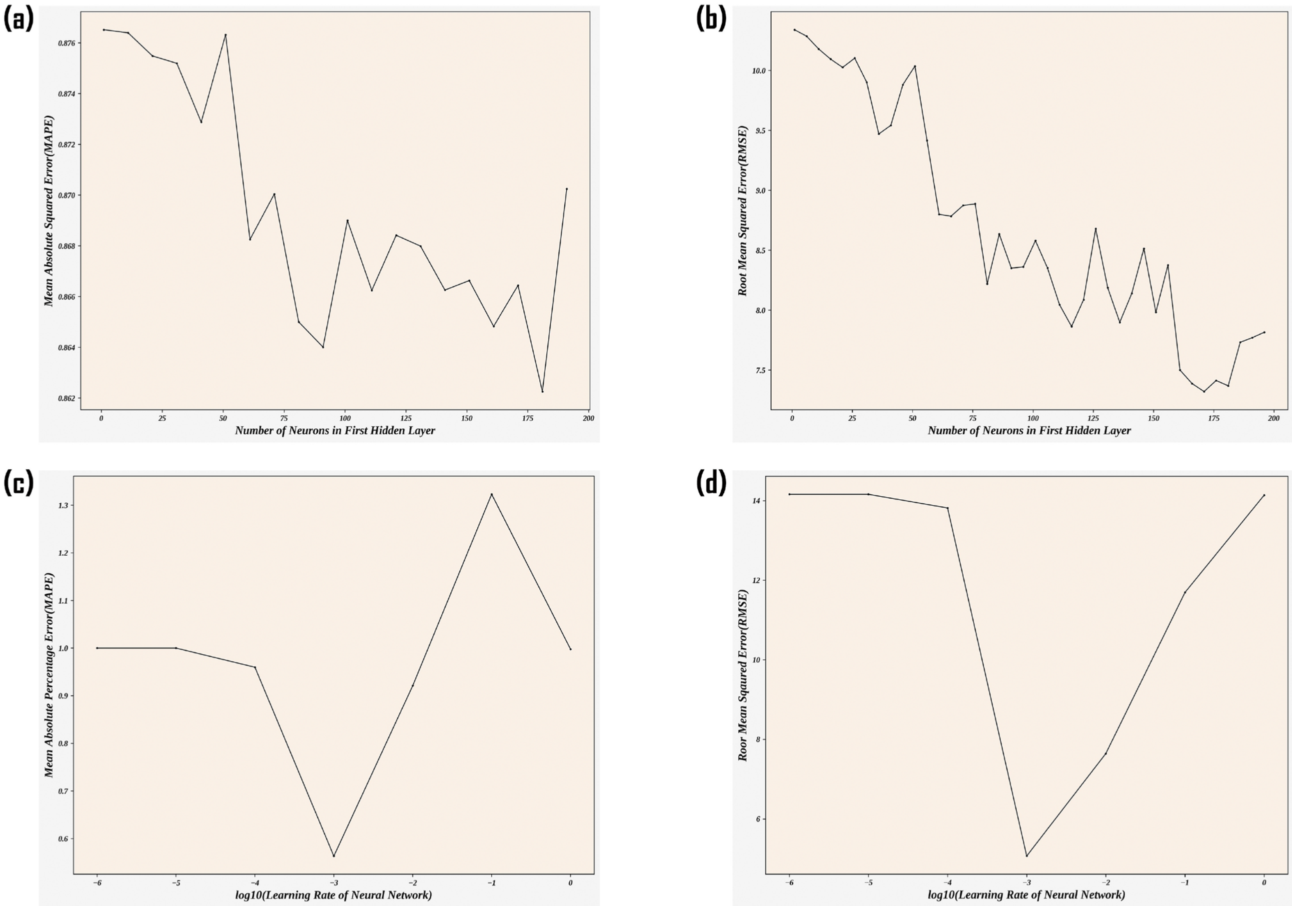


Figure 7. The effect of hyperparameters variation on deep learning network performance

work, the optimization process must be located and coordinated within the predictive process. The location, connection, and integration of the optimizer method into the predictive method are of great importance. To streamline exposition and facilitate comprehension of the optimization algorithm's integration with the deep learning architecture, a schematic representation of the workflow was presented. **Figure 8**, shows the view process of the optimized deep-learning hybrid network.

3. Results and discussion

3.1. Convergence curve

The computational structure of metaheuristic algorithms is based on searching the space of possible solutions. These algorithms randomly select a set of solutions at each stage and obtain the value of the objective function for each of them, considering the best solution available at each stage as the temporary solution to the problem at that stage. This process is repeated in subsequent stages. These iterations create a set of the best solutions. The geometric location of these solutions, in terms of the number of iterations, forms a graph that shows the state of changes in the best solutions obtained during the different stages of the algorithm. This graph is known as the convergence curve to the optimal solution or, in short, the convergence graph. The convergence graph shows the progress of the computational stages of the algorithm and the improvement of the objective function values while searching for the solution. In general, the convergence graph displays the overall behaviour of the optimization algorithm, whether the algorithm converges toward the final solution or diverges, and if it converges, the graph shows how this convergence occurs. The shape of convergence graphs can be gradual or stepwise, depending on the type of optimization process. In the stepwise type, the optimal solution value remains constant for successive iterations, and the algorithm cannot discover new optimal values in each iteration and stage, which is directly related to the computational structure of the optimization process and the type of optimization problem. The stepwise or gradual shape of the convergence graph cannot be the sole basis for judging the performance of the optimization algorithm. One of the important features of this graph is its decreasing slope. The higher the decreasing slope of the graph, the faster the algorithm discovers optimal solutions and its intelligent performance in searching for better solution space. Another important feature of this

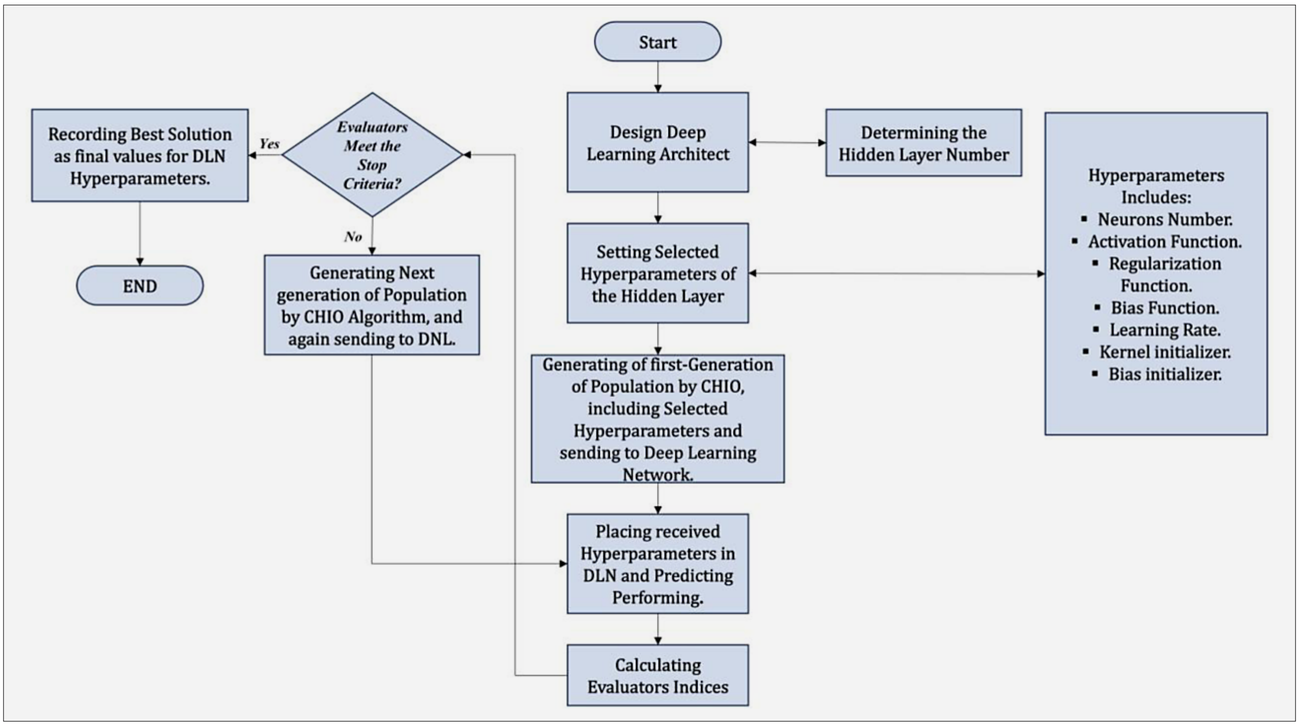


Figure 8. Process Overview of the steps taken to create an optimal deep learning network

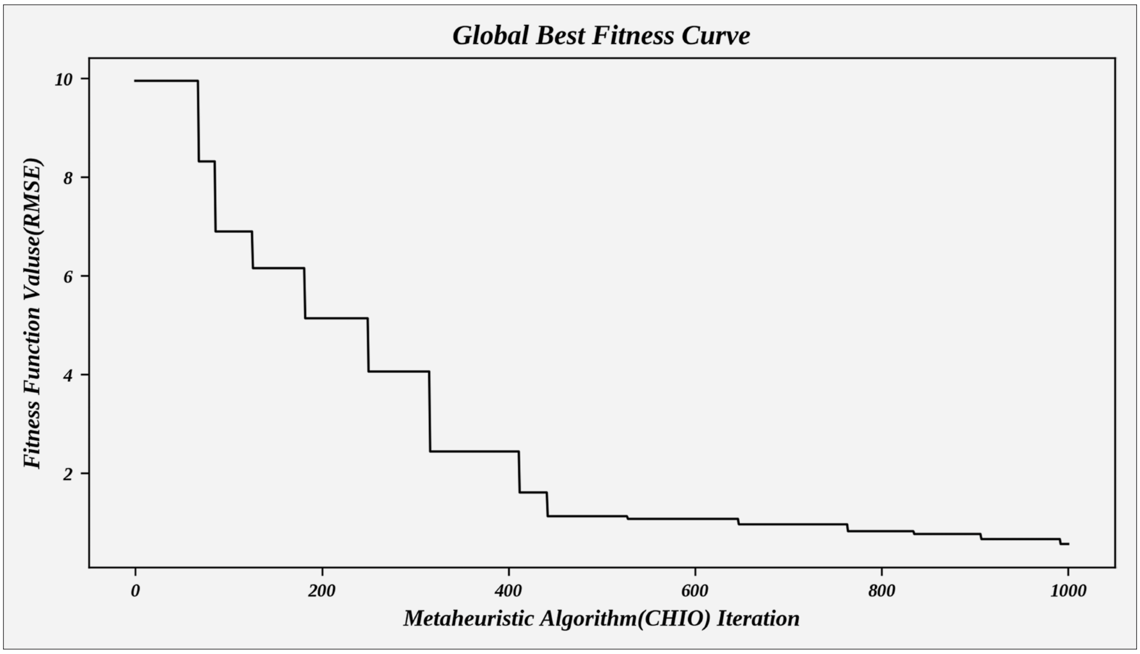


Figure 9. Convergence graph of the optimization algorithm with its iterations

graph is the final horizontal section of the graph, which indicates the stopping of the process of discovering a new optimal solution, and the iterations performed in that interval are useless calculations; to reduce the calculation time and avoid unnecessary use of the computer's computational capacity, those iterations can be ignored in the next stages. Of course, it must be ensured that the horizontal section must form the last part of the graph. The presence of oscillations in the convergence graph is generally not a good sign. These oscillations can indicate the algorithm's confusion in choosing an appropriate partition of the solution space to search for the optimal solution, which is considered a weakness of the optimization algorithm. In this case, the probability of the algorithm getting stuck in local extrema increases.

One of the important uses of this graph is to compare the performance of different optimization algorithms with each other. By considering this graph, various algo-

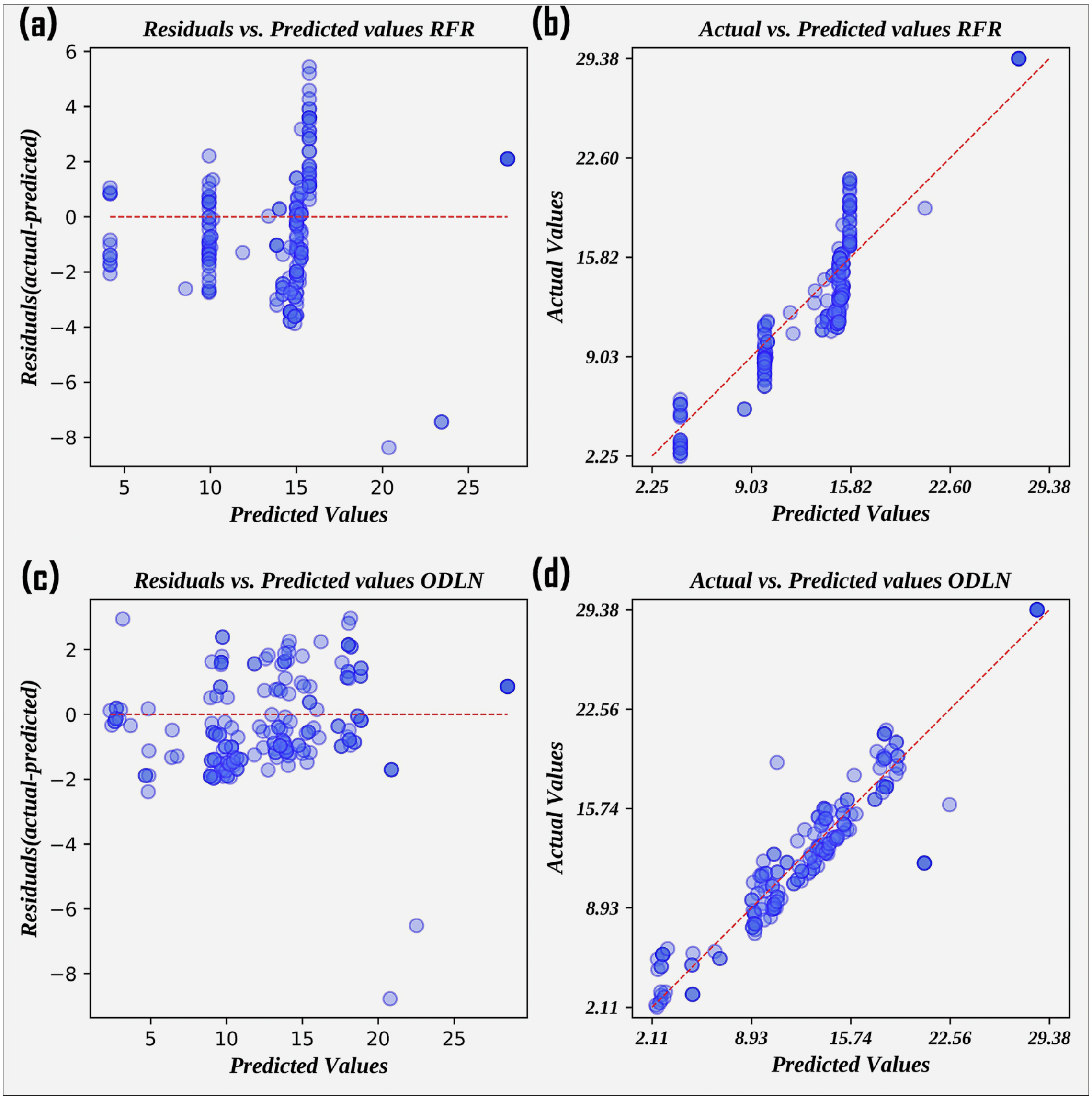


Figure 10. Correlation status of actual and predicted values (a. Random Forest, b. Optimized Deep Learning) and error value of each observation (a. Random Forest, b. Optimized Deep Learning)

rithms can be compared in terms of convergence and divergence to the optimal solution, as well as the convergence speed and shape of convergence. Furthermore, the convergence graph of the optimization algorithm can be used to adjust the hyperparameters and reach the optimal solution. This graph can also help identify problems in the optimization process and its slowness. Considering the above, drawing the convergence graph of the optimization process is very important. For this reason, the convergence pattern of the coronavirus herd immunity optimization process, which is used to optimize the deep learning network for predicting the Peak particle velocity, is plotted and given in **Figure 9**.

According to **Figure 9**, the optimization process converges to a specific solution. This indicates the correct performance of the optimized deep-learning network. The shape of the convergence graph is a step-down, indicating that the optimal solution is not reached at each step of the optimized deep learning hybrid network calculations. The size of the convergence graph platforms indicates that the speed of movement towards the optimal solution is high in the initial iterations and decreases as time passes and approaches the optimal solution, which is a normal behaviour of an optimization process. This also indicates that the number of iterations of the optimization process is sufficient. No fluctuations are observed in the pattern, which is due to the correct orientation of the optimization process in the problem solution space.

3.2. Correlation of Actual and Predicted Data

The evaluation of performance quality of behavioural models adapted to data can be evaluated from various aspects. One of the most common methods for testing the efficiency of models is the use of numerical criteria.

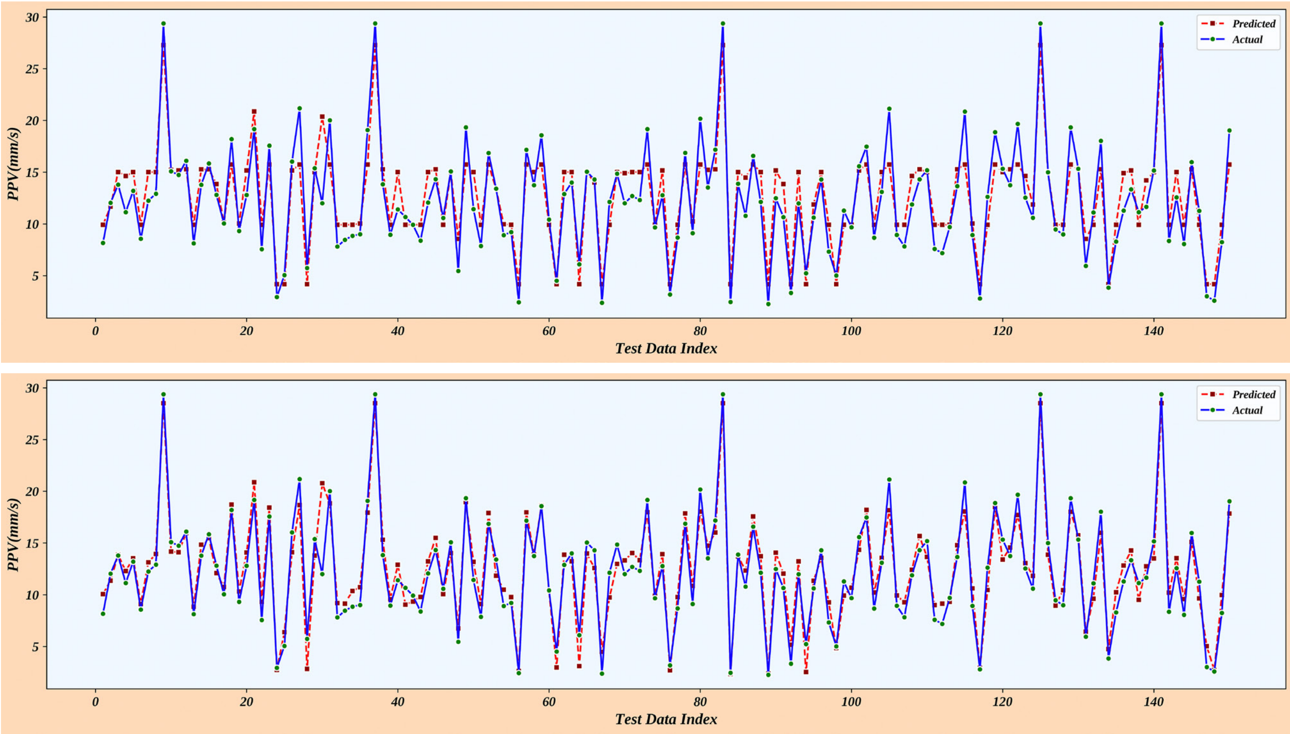


Figure 11. Compare actual and predicted values correspondingly

These criteria, according to their computational structure, evaluate and report the efficiency of a predictive model from various aspects. In addition to the weaknesses of these numerical parameters, which were mentioned in the previous section, only relying on this form of indicators can be misleading. To prevent partial judgment of the model's performance and ensure access to its real performance, in addition to using numerical criteria, graphical and diagrammatic observation of the model's performance can be beneficial. Accordingly, in this part of the present study, the efficiency of models has also been examined graphically. The residual error of each prediction is one of the most important indicators indicating the efficiency of each model, and it is not possible to make a correct and complete judgment of the quality of the model by studying its values or even its average. One of the most important graphical tools for examining the model performance is displaying the residual errors of each prediction. For this display, the data index is displayed on the horizontal axis and the residual errors of each prediction are displayed on the vertical axis. The residual error is the distance between the predicted value and the actual value. In this graph, if the model has acceptable performance, the data dispersion will have two characteristics. The residual error values of each prediction for a model with acceptable performance will have a high density around the horizontal axis, which represents zero error. However, in such models, the dispersion of the residual errors around the horizontal axis is symmetrical and their dispersion does not follow a specific pattern. Such a graphical display can show the overall performance of the model at once and help make a correct judgment. In addition to this graph, a correlation graph of the actual data and the predicted data is also presented. These two graphs together depict the model's performance. In this research work, the two aforementioned graphs have been depicted to complete the judgment process. **Figure 10** shows the prediction accuracy graphs for the stochastic gradient descent, support vector machine, adaptive reinforcement, and deep learning network models. Looking carefully at **Figure 10**, it is clear that the data density around the zero-error line for the deep learning-based model is better than other models. Also, the data symmetry around the zero-error line is more acceptable for the deep learning-based model than other models. Considering the correlation graph of the actual data and the predicted data, it also seems that the performance of the deep learning-based model is better than other models. Using the graph method helps to study the model's performance instantly and simultaneously.

Figure 11, is a line graph that graphs two datasets labeled "Predicted" and "Actual" over a test data index range from 0 to 140, with the two graphs repeated twice, likely to attract attention or for reproducibility purposes. The x-coordinate is the test data index, and the y-coordinate plots some unknown quantitative quantity between 0 and 30. The "Predicted" line is a line of constant value 25, which is an ideal or target value that is constant for all test indices. In contrast, the "Actual" line starts at 0 for the initial test index and rises slowly over time but never reaches the "Preferred" value, plateauing at 20-22—3-5

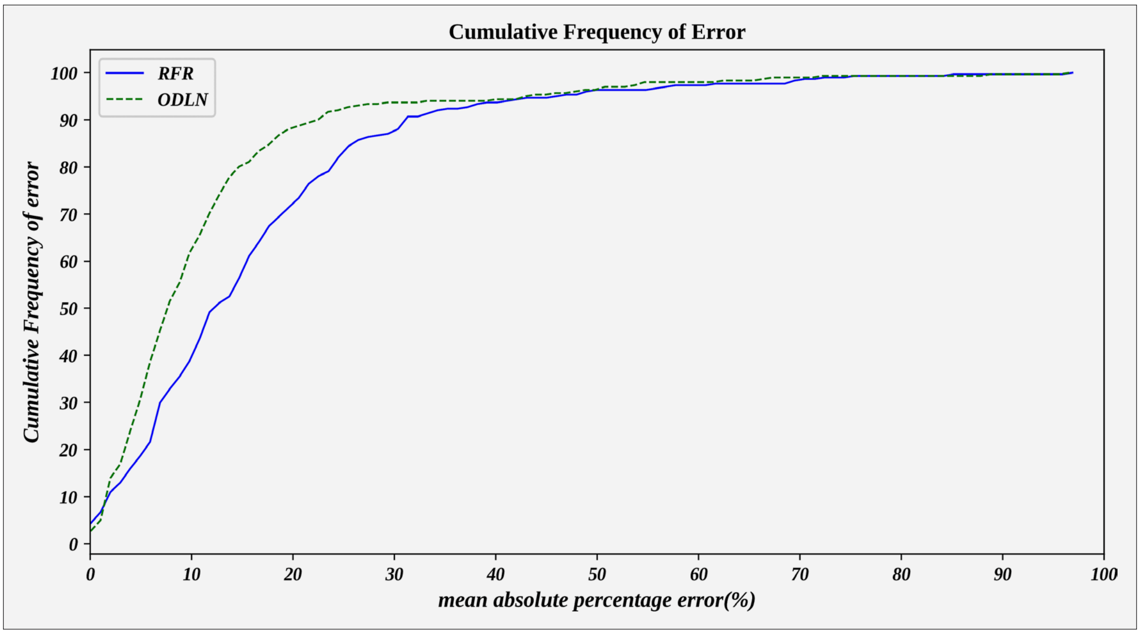


Figure 12. Cumulative frequency chart of model errors

units short of the target each time. This recurring shortage is an indicator of system underperformance, with the deficiency largest on first test indices and decreasing slowly but still considerable even on subsequent indices. The flattening of the "Actual" line is indicative of a saturation effect where decreasing returns or internal constraints make further convergence with the "Preferred" value unrealistic. The reasons may be errors in calibration (e.g. a predictive model underestimating the outcomes consistently), external constraints (e.g. lack of resources), or measurement noise. Recommendations are to verify the root cause of the plateau (e.g. model bias, feature omissions, or training issues), rescale systems as needed, and find out if the gap is tolerable or needs to be optimized further. The absence of axis markers and contextual details (e.g. domain knowledge) limits more detailed interpretation but suggests an obvious need for corrective action based on the visual trend to align "Actual" results with "Preferred" objectives. Additional context could refine the analysis further.

Examining the statistical status of errors resulting from prediction by a behavioural model can help provide confidence in the model's performance from various aspects. One of the important aspects of error in the discussion of behavioural data models is paying attention to the overall frequency of errors occurring in the prediction process. According to the definition of frequency, it refers to the number of data repetitions in defined intervals. Determining the frequency of errors in different intervals and identifying intervals with high frequency is a good reflection of the more accurate performance of the model. In this regard, using the relative cumulative frequency chart of the error population can be very helpful. About this type of criterion, it can be said that for models that perform better, the relative cumulative frequency of errors is in intervals containing the lowest errors. The graphical manifestation of this phenomenon is the stretching of the relative cumulative frequency chart towards values close to one in intervals of error values close to zero. In other words, the more the model's chart in the low error ranges moves above the charts of other models, the better the model's performance. In this research work, to complete the process of evaluating predictive models, the relative cumulative frequency of errors has been plotted against the mean absolute error. **Figure 12** shows the state of the relative cumulative frequency curve of errors based on the mean absolute error. As is clear from **Figure 12**, the curve of the deep learning-based model in the lower error ranges has presented a higher relative cumulative frequency and has moved to the upper part of the graph, indicating its better performance than the other selected models. This criterion also confirms the more stable and accurate performance of the deep learning-based model compared to other models.

3.3. Numerical results

The use of graphical methods, along with their strengths, also have weaknesses. The main weakness of graphical methods is the non-quantitative comparison of outputs. The only way to compare graphs, since they are based on visual indicators, is highly influenced by personal taste and judgment. The quality of using graphical indicators depends on the experience and knowledge of the person using them. This makes it difficult to use these types of graphs for judgment. To overcome this weakness, using a graphical criterion and matching it with a numerical index can be very useful. For this purpose, displaying actual and predicted data simultaneously is a common tool. To achieve such a graph, actual and predicted data are plotted based on a data index, indicating the degree of data matching. If the model performs well, the two lines passing through the actual and predicted data will be very close to each other and the distance between them will be small. However, in the event of large errors, the degree of separation between the two graphs will increase. This same criterion can be used to quantitatively compare the performances of models. For this purpose, after drawing lines passing through the actual data and the predicted data, the size of the area between the two lines was used as a quantitative indicator to compare the performance of the models and compare the graphs. Accordingly, the lines passing through the actual data and the predicted data for the different selected models are shown in **Figure 11**. In **Figure 11**, it is clear that the deep learning network-based model performs better and the separation between lines appears to be less than other models. However, for a more accurate judgment, the area between the two lines has been calculated. Based on the calculated values, it is also clear that the separation between the lines for the model based on the deep learning is equal to 30.459, which is the best condition compared to other models. This indicates a high agreement between the actual output data and the predicted data, which is a reliable criterion for measuring and selecting the best model.

3.4. The mean absolute percentage error

The mean absolute percentage error is one of the most common statistical measures for studying the behaviour of predictive models. The computational nature of this measure comes with certain characteristics that, while reflecting the degree of deviation of predicted values from actual values, sometimes should be interpreted with caution. This indicator can be easily calculated which is one of its strengths. Equation 4 shows its computational formula.

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \tag{4}$$

Where:

y_i – measured values (mm/s),

$\hat{y}_i$ – predicted values (mm/s),

n – amount of data.

The mean absolute percentage error is a measure of the model's accuracy. Since this measure is reported in percentage terms, it is easier to interpret and present than other indicators. Despite the strengths stated, this indicator has its unique weaknesses that must be considered while interpreting the results. The mean absolute percentage error, due to its computational structure, loses its computational power when faced with real zero values since division by zero has no mathematical meaning. This indicator sometimes evaluates models of poor quality that lack sufficient accuracy and precision as good models by calculating their low values. One of the main limitations of this indicator is that as the actual and predicted values approach zero, despite the closeness of the actual and predicted values, the error-index value moves towards high values. This measure is sensitive to the scale in which the data is located. Therefore, using this index for non-scalar data can lead to errors in evaluating the actual performance of the predictive model. Accordingly, using this index to compare the performance of a model when faced with different data is not logical. Therefore, it is always recommended to use other indices, along with this criterion, for a comprehensive evaluation of the predictive model.

In this research, the average absolute error percentage was calculated to evaluate the efficiency of the deep learning-based model. **Figure 13a** shows the average absolute error percentage values obtained for the deep learning model and the support vector machine, adaptive boosting, and stochastic gradient descent models. Considering the average absolute error percentage value, 0.068, it is clear that the deep learning-based model has provided the lowest average absolute error percentage. In the meantime, the support vector machine-based model has provided better performance by a minimal distance. According to the results obtained for these models, and considering the processed nature of the data, the deep learning model has shown acceptable performance in predicting the amount of vibration generated based on the distance and amount of explosives used.

3.5. Coefficient of determination

A high correlation between measured values and predicted values by models is an indication of their acceptable performance. To study the amount of both behaviour and correlation between predicted and actual data, there is an index called the coefficient of determination (R^2). The coefficient of determination; in its basic definition, is a measure of the quality of the data fit to a behavioural model. However, in the behavioural prediction workspace, it indicates how close the actual values and predicted values are, or more precisely, the degree of their correlation. To calculate the value of the coefficient of determination, we can use **Equation 5**.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)}{\sum_{i=1}^{n}(y_i - \bar{y})} \tag{5}$$

Where:

$\bar{y}$ – mean of the actual data values (mm/s).

The rest of the parameters have been previously introduced. The coefficient of determination indicates to what extent the observed values match the predicted behavioural model. In general, the values of the coefficient of determination range from 1 to negative infinity. Values close to one usually indicate acceptable performance of the behavioural model, and values close to zero and even negative values indicate unacceptable performance of the model in predicting the behaviour of the data. This index, like other criteria for measuring the efficiency of predictive behavioural models, has its weaknesses and limitations. Factors such as data scale, data nature, and data preprocessing methods are among the factors affecting the behaviour of the coefficient of determination index. Accordingly, in some cases, high values of this index can be due to errors in the model. The presence of outliers indicates the unreliability of the coefficient of determination. Because the coefficient of determination is very sensitive to the presence of outliers. The co-linearity phenomenon between sharp input data can cause the coefficient of determination to be high, and as a result, cover the real weakness of the model. It should also be noted that the coefficient of determination does not provide any interpretation for the cause of the model behaviour and the roots and origins of errors. Therefore, the quality of the predictive model can be examined by this index and others. Given the importance of this index and its limitations, the coefficient of determination for the selected predictive models has been calculated and its values are presented in **Figure 13b**. In **Figure 10b**, it is clear that the behavioural model based on deep learning, with a coefficient of determination of 0.972, has performed best. Considering the data scaling and the removal of outliers and the examination of the absence of the co-linearity phenomenon, it can be stated that the coefficient of determination value is a reliable expression and reflection of the model performance.

3.6. Root mean squared error

The scatter of measured data around the predicted behavioural model is also important in studying the quality of a predictive behavioural model. The root mean square error index is a measure of the behaviour of the model. The root mean square error index is an index that reflects the standard deviation of the residuals of the actual values from the predicted values. This measure is a parameter that is not standardized in terms of the scale of errors that occurred in the prediction process, however, the coefficient of determination is a standardized index. The values of the root mean square error index start from zero and move towards positive infinite values. Naturally, considering the type of index, values close to zero are considered desirable values. To calculate the value of the root mean square error-index, **Equation 6** can be used.

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(y_i - \hat{y}_i)^2}{n}} \tag{6}$$

In addition to providing conditions for the alignment of actual and predicted data, the root mean square error-index, by emphasizing and magnifying large model errors, helps identify areas of the data where the model does not behave acceptably. Due to this feature, this index takes a more conservative approach compared to other indices and is considered more reliable. The root mean square error considers more weight for larger errors. This index separates the root mean square error from the mean absolute error and makes it more sensitive to outliers. The root mean square error index results from squaring the distance between the actual values and the predicted values. Of course, it should be noted that the root mean square error is also non-equilibrium and the data has a negative effect. The root mean square error was used to evaluate the performance of the model. Accordingly, **Figure 13a** shows different values of the root mean square error for the selected predictive models. Considering **Figure 13a**, the optimized deep learning-based model has provided more acceptable performance than the other models. The root mean square error value for the deep learning-based model is 0.836, which is an indicator of the smaller computational errors of the behavioural model.

3.7. Model Bias and variance

Bias and variance of predictive models are among the most important evaluation indicators, indicating the degree of generalizability. Bias is an indicator that shows the model's accuracy in tracking the general behaviour of the data. A low bias value indicates that the model has successfully determined the general trend of the data by overcoming data noise. On the other hand, if the model fails to track the general trend of the data, data noise is high and the model is unable to overcome it, thus, the model has a high level of variance. The interaction of these two parameters and reaching the equilibrium point of variance and bias is important for having a good predictive model. As the bias increases, the model's performance in predicting values for both training and test data will be poor. As the complexity of the model and its fit to the data increase, the bias will move towards lower values. The model performance variance is examined in the model training process, indicating the data fluctuation. A high variance indicates overfitting of the model in the training phase and the dominance of outlier data over the model behaviour. It shows that the model performs very well in the training phase but very poorly on tests and new data.

Given the nature of these two model parameters, it will provide reliable and generalizable results providing the minimum possible value for the two bias and variance indices. It is worth noting that with increasing model complexity, the model bias decreases, but, causes prefitting of the model, thus, the model variance will increase, which is undesirable for the model. Therefore, reaching an equilibrium point where both the bias and variance of the model have the lowest possible values is very important.

Considering the above explanations in this research work, to achieve a better judgment regarding the perfor-

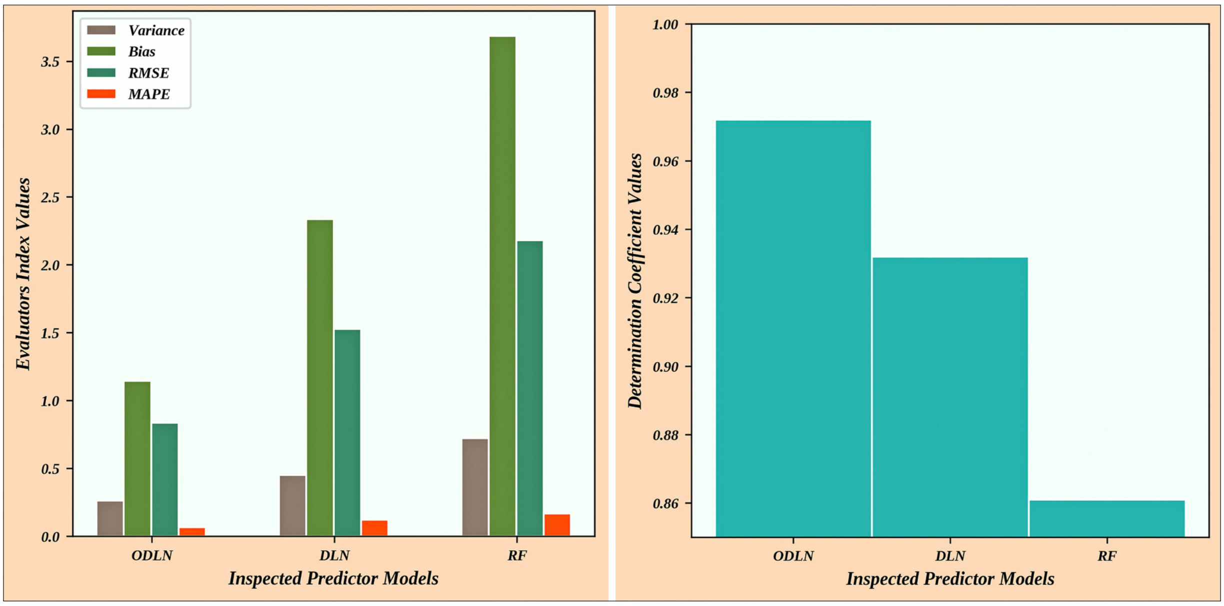


Figure 13. Values of various model evaluation indicators

mance of the models, the bias and variance of the models were also calculated. **Figure 13a** shows the values obtained for the three models. The model based on the optimal deep learning network presented the lowest point of balance of bias and variance, which is another proof of its better and more stable performance.

4. Conclusions

This study developed and validated a new hybrid model to predict blast-induced peak particle velocity (PPV) by combining a deep learning (DL) network with the Coronavirus Herd Immunity Optimizer (CHIO), a metaheuristic algorithm. The key innovation is using CHIO to automatically tune the DL model's hyperparameters—such as the number of hidden layers, neuron layout, activation functions, and learning rate—replacing slow, manual trial-and-error tuning. This automated search produced a more reliable model with better generalization. We tested the model on a strong dataset of more than 1,000 blast records from the Songun Ahar and Golgohar Sirjan mines. The hybrid approach outperformed standard methods, achieving an R^2 of 0.972, RMSE of 1.146, and MAPE of 0.068—at least a 4% improvement in accuracy compared with benchmarks like Random Forest and a non-optimized DL network. Practically, this tool can help mine engineers predict vibration levels more accurately, design safer blast patterns, and reduce environmental impacts while meeting strict safety standards. Methodologically, the work offers a useful blueprint for tackling other complex, nonlinear geomechanical problems where classic empirical formulas don't suffice. We also outlined paths for future research. The current model mainly uses distance and explosive charge as inputs; adding geomechanical variables (for example, rock mass rating and joint properties) and blast-design parameters (such as delay timing and stemming) should improve performance. The model should also be validated across different geological settings and mining methods to confirm its scalability and robustness. Overall, this research lays the groundwork for next-generation AI decision-support systems in mining and points toward integrating these models with real-time sensors and IoT platforms for smarter, dynamic excavation management.

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SAŽETAK

Procjena vršne brzine čestica izazvane miniranjem primjenom optimiziranoga dubokog učenja s algoritmom optimizacije kolektivnog imuniteta koronavirusa

Rudarstvo je jedan od najvažnijih gospodarskih sektora. Površinski kopovi najčešći su oblik eksploatacije, a miniranje je najučinkovitija metoda razaranja stijenske mase. Međutim, ovaj postupak može uzrokovati znatna oštećenja uslijed vibracija. Stoga su praćenje i kontrola vibracija od ključne važnosti. Cilj je ovoga istraživanja procjena razine vibracija na temelju udaljenosti od mjesta miniranja i količine upotrijebljenoga eksploziva. U tu svrhu vibracije su procjenjivane pomoću najveće brzine čestica (*Peak Particle Velocity* – PPV) mjerene seizmografima. Mjerenja su provedena u dvama velikim površinskim kopovima u Iranu, u kojima je prikupljeno približno 1000 podataka. S obzirom na složenost prikupljenih podataka, za modeliranje je primijenjena metoda dubokoga učenja (*deep learning*). Ova metoda sadržava velik broj hiperparametara, čija pravilna prilagodba znatno utječe na učinkovitost modela. Za određivanje optimalnih vrijednosti korišten je algoritam optimizacije kolektivnoga imuniteta koronavirusa (*Coronavirus Herd Immunity Optimizer* – CHIO), algoritam inspiriran biološkim principima imunološkoga odgovora populacije na virusne infekcije. Učinkovitost modela ispitana je primjenom različitih kriterija. Rezultati pokazuju da je primjenom metode optimizacije točnost predviđanja poboljšana za najmanje 4 %. Koeficijent determinacije za modele slučajne šume (*random forest*), osnovnoga dubokog učenja i optimiziranoga modela iznosio je 0,861, 0,932 i 0,972. Vrijednosti korijenske srednje kvadratne pogreške (RMSE) bile su 3,687, 2,338 i 1,146, dok su indeksi prosječne apsolutne postotne pogreške (MAPE) iznosili 0,169, 0,128 i 0,068. Zaključeno je kako metoda dubokoga učenja pokazuje zadovoljavajuću izvedbu, a njezina se učinkovitost može dodatno povećati primjenom algoritama optimizacije. Dobiveni rezultati potvrđuju izvrsnu učinkovitost integracije CHIO metode i njezinu visoku primjenjivost u procjeni vibracija uzrokovanih miniranjem.

Ključne riječi:
miniranje, vršna brzina čestica, umjetna inteligencija, duboko učenje, kolektivni imunitet, koronavirus

Authors' contribution

Davood Mohammadi Sargini; (PhD Candidate, Shahrood University of Technology): participated in all work stages such as sample presentation, experimental tests, data analysis, writing and editing the article, and all project costs. **Mohammad Ataei**; (Professor, Shahrood University of Technology): shared contributions throughout the whole process and data analyses. **Reza Mikaeil** (Associate Professor, Urmia University of Technology): supervised the project and contributed to the writing and editing of the paper. **Akbar Esmaeilzadeh** (Assistant Professor, Urmia University of Technology): participated in all work stages such as sample presentation, experimental tests, data analysis, writing and editing the article.
All authors have read and agreed to the published version of the manuscript.