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Forecasting $PM_{2.5}$ emissions in open-pit minesusing a functional link neural network optimized by various optimization algorithms

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Abstract

$PM_{2.5}$ air pollution is not only a significant hazard to human health in everyday life but also a dangerous risk to workers operating in open-pit mines OPMs), especially open-pit coal mines (OPCMs). $PM_{2.5}$ in OPCMs can cause lung-related (e.g., pneumoconiosis, lung cancer) and cardiovascular diseases due to exposure to airborne respirable dust over a long time. Therefore, the precise prediction of $PM_{2.5}$ is of great importance in the mitigation of $PM_{2.5}$ pollution and improving air quality at the workplace. This study investigated the meteorological conditions and $PM_{2.5}$ emissions at an OPCM in Vietnam, in order to develop a novel intelligent model to predict $PM_{2.5}$ emissions and pollution. We applied functional link neural network (FLNN) to predict $PM_{2.5}$ pollution based on meteorological conditions (e.g., temperature, humidity, atmospheric pressure, wind direction and speed). Instead of using traditional algorithms, the Hunger Games Search (HGS) algorithm was used to train the FLNN model. The vital role of HGS in this study is to optimize the weights in the FLNN model, which was finally referred to as the HGS-FLNN model. We also considered three other hybrid models based on FLNN and metaheuristic algorithms, i.e., ABC (Artificial Bee Colony)-FLNN, GA (Genetic Algorithm)-FLNN, and PSO (Particle Swarm Optimization)-FLNN to assess the feasibility of $PM_{2.5}$ prediction in OPCMs and compare their results with those of the HGS-FLNN model. The study findings showed that HGS-FLNN was the best model with the highest accuracy (up to 94–95 % in average) to predict $PM_{2.5}$ air pollution. Meanwhile, the accuracy of the other models ranged 87 % to 90 % only. The obtained results also indicated that HGS-FLNN was the most stable model with the lowest relative error (in the range of −0.3 to 0.5 %).

Keywords

open-pit coal mine, air pollution, dust, $PM_{2.5}$, human health, hunger games search, functional link neural network, optimization, Coc Sau open-pit coal mine, Quang Ninh province, Vietnam

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For citation

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ТЕХНОЛОГИЧЕСКАЯ БЕЗОПАСНОСТЬ В МИНЕРАЛЬНО-СЫРЬЕВОМ КОМПЛЕКСЕ И ОХРАНА ОКРУЖАЮЩЕЙ СРЕДЫ

Научная статья

Прогнозирование выбросов пыли ($PM_{2.5}$) на угольных разрезах с помощью нейронной сети с функциональными связями, оптимизированной различными алгоритмами

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Аннотация

Загрязнение воздуха $PM_{2.5}$ (твердые частицы размером 2,5 мк и менее) представляет собой не только значительную опасность для здоровья человека в повседневной жизни, но и опасный риск для рабочих при открытых горных работах, особенно на угольных разрезах. $PM_{2.5}$ на угольных разрезах могут вызывать заболевания легких (например, пневмокониоз, рак легких) и сердечно-сосудистые заболевания из-за длительного воздействия вдыхаемой пыли. Поэтому точное прогнозирование $PM_{2.5}$ имеет большое значение для минимизации загрязнения $PM_{2.5}$ и улучшения качества воздуха на рабочих местах. В данном исследовании изучались метеорологические условия и выбросы $PM_{2.5}$ на угольном разрезе во Вьетнаме с целью разработки новой интеллектуальной модели для прогнозирования выбросов и загрязнения $PM_{2.5}$, применялась нейронная сеть с функциональными связями (FLNN) для прогнозирования загрязнения $PM_{2.5}$ в зависимости от метеорологических условий (в частности, температуры, влажности, атмосферного давления, направления и скорости ветра). Вместо традиционных алгоритмов для обучения модели FLNN был использован алгоритм поиска методом голодных игр (HGS). Важнейшая роль HGS в данном исследовании заключается в оптимизации весов в модели FLNN, которая была названа моделью HGS-FLNN. Также были рассмотрены три другие гибридные модели, основанные на FLNN и метаэвристических алгоритмах, т.е. ABC (искусственная пчелиная колония)-FLNN, GA (генетический алгоритм)-FLNN и PSO (оптимизация роя частиц)-FLNN, для оценки возможности прогнозирования $PM_{2.5}$ на угольных разрезах и сравнения их результатов с результатами модели HGS-FLNN. Исследования показали, что HGS-FLNN является лучшей моделью с самой высокой точностью прогнозирования загрязнения воздуха $PM_{2.5}$ (в среднем до 94–95 %, при этом точность других моделей варьировалась от 87 до 90 %), а также наиболее стабильной моделью с наименьшей относительной ошибкой (в диапазоне от −0,3 до 0,5 %).

Ключевые слова
угольный разрез, загрязнение воздуха, пыль, $PM_{2.5}$, здоровье человека, поиск методом голодных игр, нейронная сеть с функциональными связями, оптимизация, разрез Кок Сау, провинция Куангнинь, Вьетнам

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Для цитирования
Bui X.-N., Nguyen H., Le Q.-T., Le T.-N. Forecasting $PM_{2.5}$ emissions in open-pit mines using a functional link neural network optimized by various optimization algorithms. *Mining Science and Technology* (*Russia*). 2022;7(2):111–125. https://doi.org/10.17073/2500-0632-2022-2-111-125

Introduction

"Mining is not everything, but without mining, everything is nothing", Max Planck, famous German theoretical physicist, said. Practically everything, for example, metals, cement, construction materials, bridges, glass, towers/buildings, coal, power plans, etc., originate initially from mining. Such activities have a positive economic effect on development of countries worldwide and energy security of each country. However, mining operations also have significant negative environmental impacts, especially air pollutants (e.g., total suspended particulate (TSP), inhalable dust particles with diameters that are generally 1.0, 2.5, and 10 micrometers and smaller ($PM_{1.0}$, $PM_{2.5}$, PM_{10})) [1–3] Fig. 1). Open-pit mines (OPMs) have a more serious environmental impact compared with underground mines because of the outdoor work implementation. Depending on the particle size, the adverse effects on human health and occupational exposure may be more or less significant [4, 5]. Among the particles generated by OPM operations, OPCM-produced particles are considered as the most dangerous due to their different sizes and chemical and mineralogical composition (e.g., coal, minerals, organic compounds, etc.) [6].

In OPCMs, many activities can produce dust (i.e., $PM_{2.5}$), for instance, drilling, blasting, excavation, hauling, and transportation among others. The dust impact radius can increase due to specific meteorological conditions (e.g., wind direction and speed). In recent years, with exponential increase in energy consumption, OPCM operation has deepened to increase coal production [8]. Deeper OPCMs are unable to use natural ventilation efficiently. This results in availability of huge amount of thin particles in mining medium. These particles can be dangerous for miners and cause severe health impacts [9, 10].

To manage OPM dust emission, many researchers have measured and analyzed the amount of PM of different sizes, in order to evaluate the impacts of PM depending on size. They have proposed solutions for reductions of air pollution [11–13]. Dr. Emanuele Caudaet al. (NIOSH Center for Direct Reading and Sensor Technologies) investigated the distribution of PMs from different sources, and their findings showed that coal mine dust emission is a significant PM source (Fig. 2), and its forecast and control is an actual challenge.

Another approach to solving the dust pollution problem is estimating/forecasting the dust emission/concentration in OPCMs. Most historical studies related to PM emissions from OPCM have focused on estimating PM concentration in these operations [14, 15]. In recent years, artificial intelligence (AI) has

Fig. 1. Open-pit mines air pollution from various sources:
a – Transportation air pollution [7]; *b* – Shovel air pollution; *c* – Air pollution by various operations; *d* – Blasting air pollution

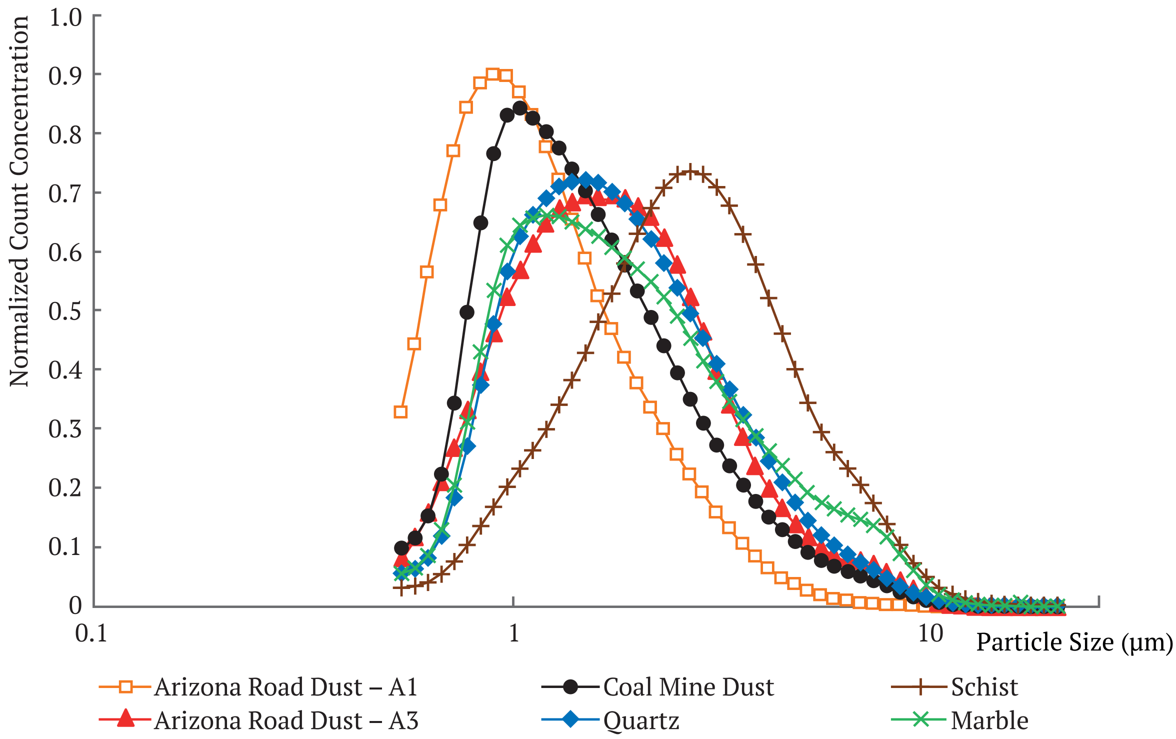

Fig. 2. Distribution of dust from various sources by size
Source: Nanozen (the official site). Dust specific calibrated real-time particle monitors.
https://nanozen.com/nanozette-q120/[Accessed: 03/10/2021]

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been widely applied to predict dust concentrations/emissions in OPM. It is also recommended as a robust tool for use in other sectors [16–20]. In the aims of forecasting OPCM air pollution Lal B. and Tripathy S.S. [21] applied a multiple layers perceptron (MLP) neural network model to predict dust concentration in an Indian OPCM. Their study confirmed the high accuracy of the MLP model in predicting dust concentration. Bakhtavar E. et al. [22] also applied an artificial causality-weighted neural network (ACWNN) model for predicting OPM blasting dust emissions. They applied a fuzzy cognitive map to extract the weights of inputs for the dust emission prediction neural network. However, the study only predicted horizontal and vertical dust distributions. Considering other activities in OPCM (i.e., drilling), Bui H.-N. et al. [23] predicted PM10 emission by means of the support vector regression model optimized by particle swarm optimization (PSO). Using deep learning technique (e.g., long short-term memory – LSTM), Li L. et al. [24] predicted the $PM_{2.5}$ and PM_{10} emissions in OPMs at RMSE (root-mean-square error) of 29.517 and 23.204, MAPE (mean absolute percentage error) of 11.573 % and 8.537 %, respectively. Lu X. et al. [25] proposed a hybrid PSO-GBM (Gradient Boosting Machine) model for forecasting $PM_{2.5}$ concentrations based on other machine learning algorithm. High convergence was observed in their study with the correlation coefficient ranged 0.920 to 0.942.

The dust concentrations/emissions were studied in terms of measurement and prediction. In most cases they were measured and forecasted based on single activity in OPMs. Although several AI models were proposed and successfully applied to forecasting dust emissions/concentrations, their validity was limited due to the range of meteorological conditions in different areas and the robustness of different intelligent models. In OPMs, $PM_{2.5}$ was evaluated as much more dangerous than PM10 in the working environment. They can cause restrictive respiratory disorder and diseases related to lung and cardiovascular system [26–28]. Therefore, in this study we designed an air quality evaluation intelligent system to measure $PM_{2.5}$ emission in OPMs. We used the internet of things method for data transfer to workstations. Subsequently, a novel hybrid-neural network model based on functional linked neural network (FLNN) and hunger games search (HGS) algorithm, abbreviated as HGS-FLNN model, was developed, in order to forecast $PM_{2.5}$ emission in a deep OPCM. It is worth mentioning that the proposed HGS-FLNN model was never developed and applied previously for forecasting OPM dust emission. The obtained HGS-FLNN model results were then compared with three other hybrid models, i.e., ABC (artificial bee colony)-FLNN, GA (genetic algorithm)-FLNN, and PSO-FLNN to highlight outstanding performance of the HGS-FLNN model.

1. Data collection

In order to estimate $PM_{2.5}$ emission in OPMs, the Coc Sau OPCM in Vietnam was investigated (Fig. 3). This is one of Vietnam's largest and deepest OPCMs with a depth of 300m below sea level in July 2021[1]. Due

[1] Coc Sau Coal Company. Summary report of production in 2021, Coc Sau. 2021 (In Vietnamese).

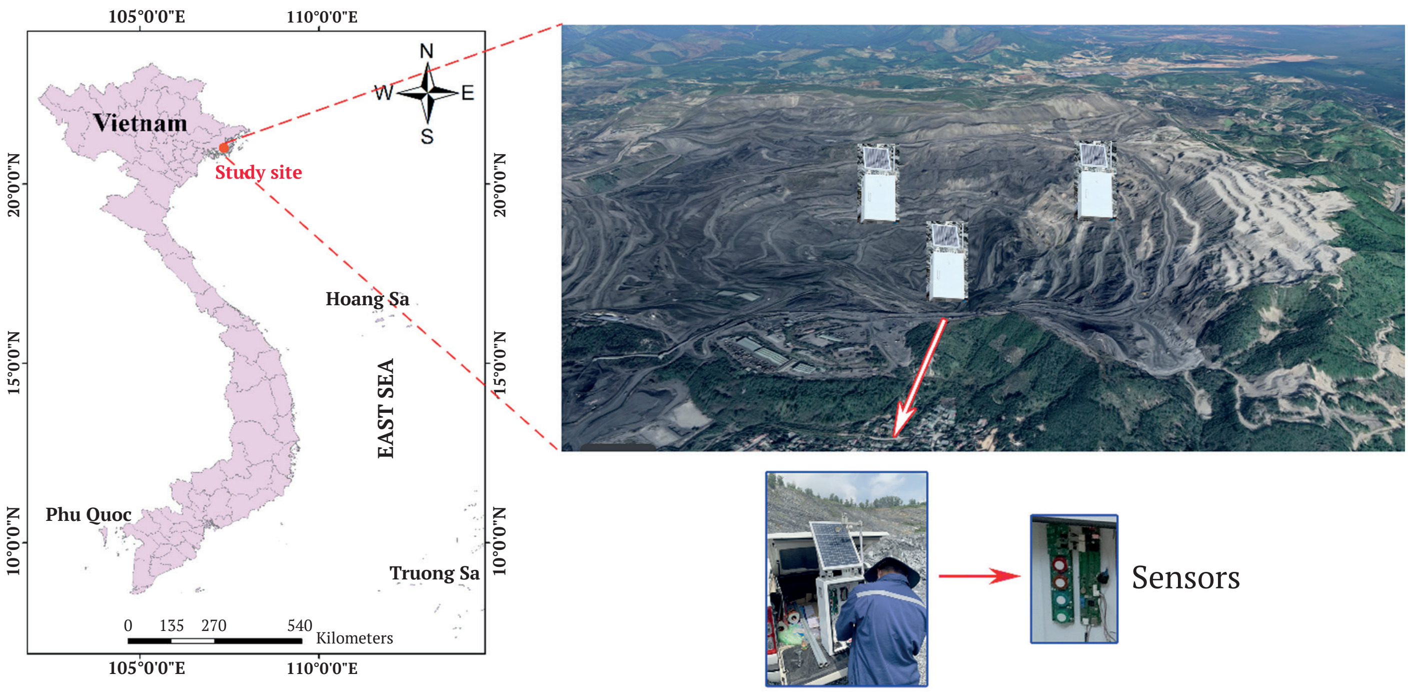

Fig. 3. Study area and air quality measurement stations locations

to the irregular shape and great depth, the mine air quality, especially in terms of $PM_{2.5}$, is very bad. Due to the great depth, the mine is unable to use natural ventilation. Therefore, the impact of high $PM_{2.5}$ concentrations is significant. As described above, $PM_{2.5}$ is one of the most adverse particles capable of causing occupational diseases. Hence, predicting $PM_{2.5}$ in this mine is aimed at finding suitable solutions to reduce the air pollution (e.g., $PM_{2.5}$) in the mine working environment.

In the aims of developing AI models to predict $PM_{2.5}$, the dataset was collected using three measuring stations (Fig. 3). Each station was designed as an air quality measuring system capable of measuring not only $PM_{2.5}$ but also meteorological conditions, such as temperature (T), atmospheric pressure (AP), humidity (H), wind direction and speed (WD, WS). These stations measured all the parameters hourly and transferred the data to the mine's technical department via the 4G network. Historical studies indicated that meteorological conditions significantly affect OPM dust emission [29, 30]. Therefore, they were used as the input variables to predict $PM_{2.5}$ in the present study. Since the mine geometry does not change significantly with deepening, the mine $PM_{2.5}$ pollution over the operation time is considered to be stable. It is worth noting that WD (e.g., West, East, North, South) was converted to numeric for solving regression problem in this study. The dataset is presented in Table 1.

Table 1

$PM_{2.5}$ emission and meteorology conditions in the study area

Category	$PM_{2.5}$	T	H	AP	WD	WS
Min.	10	18.5	83.4	985.5	1	0.1
1st Qu.	23	22.4	91.7	1,000.3	3	2.4
Median	34	23.4	94.7	1,004.4	10	3.3
Mean	34.98	23.43	94.3	1,004.3	8.534	3.285
3rd Qu.	44	24.5	97.1	1,008.2	12	4.2
Max.	90	28.8	100	1,023.9	16	7.5

2. HGS-FLNN model design for predicting $PM_{2.5}$

In the aims of predicting $PM_{2.5}$, FLNN, a kind of ANN, was selected as a single-layer architecture in this study [31, 32]. The unique mechanism of this network is based on the input variables and non-linear functional expansions [33]. It can generate hidden neurons and calculate the sum of weights. This approach enables complexity associated with regression problems [34] to be reduced. For training the FLNN model, the simple least mean square (LMS), back propagation (BP), or gradient descent-based methods can be applied to update the model's weights. The FLNN model architecture is illustrated in Figure 4.

The FLNN model (Figure 4) has many nodes generated with a large number of weights. In connection with this, updating weights to the network is challenging for a FLNN model with traditional training

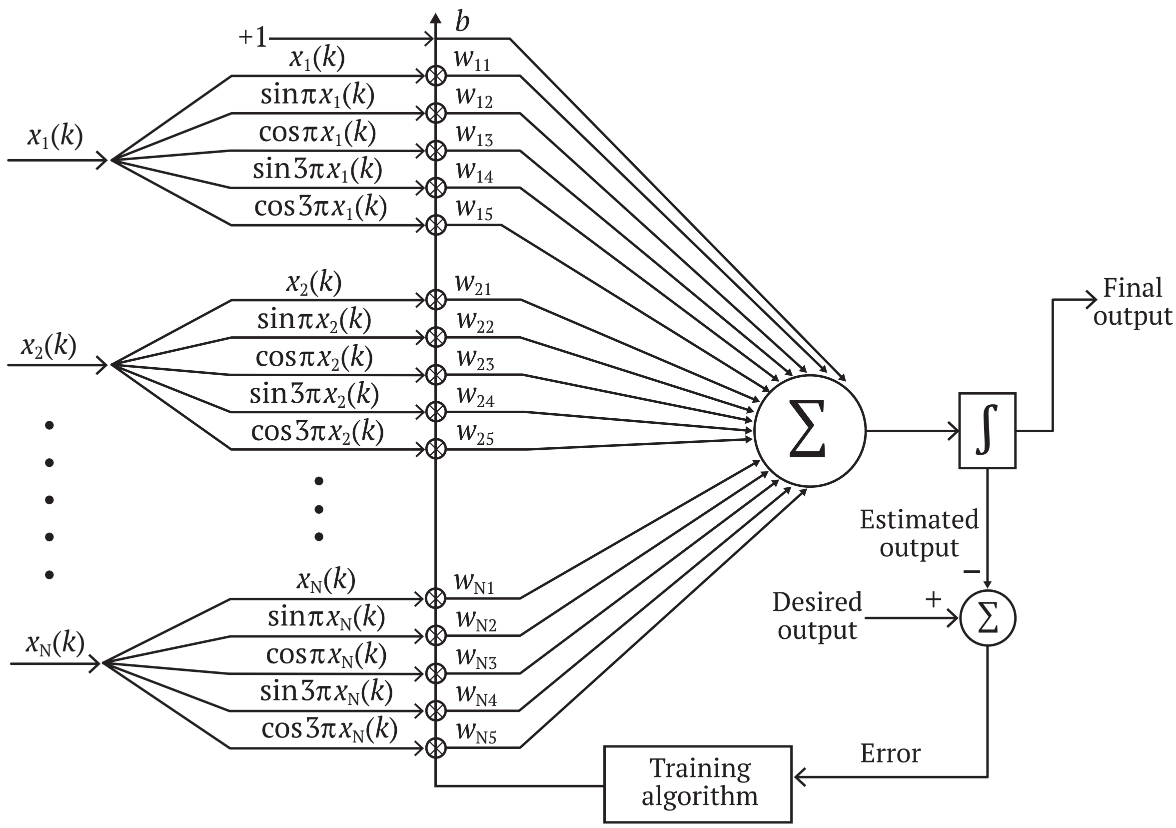

Fig. 4. FLNN model architecture

algorithms (e.g., BP, LMS) [35]. Local optima may occur while training the FLNN model with traditional training algorithms. This can reduce FLNN model performance in predicting $PM_{2.5}$.

In order to overcome this problem, optimization algorithms can be used for network training in the aims of optimizing the FLNN model weights. Metaheuristic algorithms are a good choice since they enable the FLNN model to reach the global optimum [36, 37]. In this study, HGS, a new metaheuristic algorithm proposed by Yang Y. et al. [38], was selected to train the FLNN model instead of traditional algorithms. The HGS is highly competitive algorithm in resolving optimization problems [39]. It was designed on the basis of hunger-driven activities of individuals in a swarm while hunting prey or looking for food. The HGS details are available in the original study [38]. The HGS flowchart is presented in Figure 5.

A novel hybrid AI model was designed based on the FLNN and the HGS algorithm for predicting $PM_{2.5}$ in OPCMs, referred to as the HGS-FLNN model. The HGS algorithm was developed and used to train and generate the weights for the FLNN model based on hunger-driven activities. Subsequently, the weights were updated for the network, and the model error was calculated. While optimizing the FLNN model for predicting $PM_{2.5}$, RMSE was used as the loss function for evaluating the model's performance, to determine whether the criterion is met or not. The proposed HGS-FLNN model framework is presented in Figure 6.

3. Development of the HGS-FLNN model for predicting $PM_{2.5}$

The HGS-FLNN model for predicting OPCM $PM_{2.5}$ was developed as described in Figure 6. Before developing the HGS-FLNN and other models, the dataset was randomly divided into two parts in the ratio of 4:1 for developing and testing the models, respectively. In addition, the datasets were also normalized by scaling between 0 and 1, in order to improve the models accuracy and minimize errors.

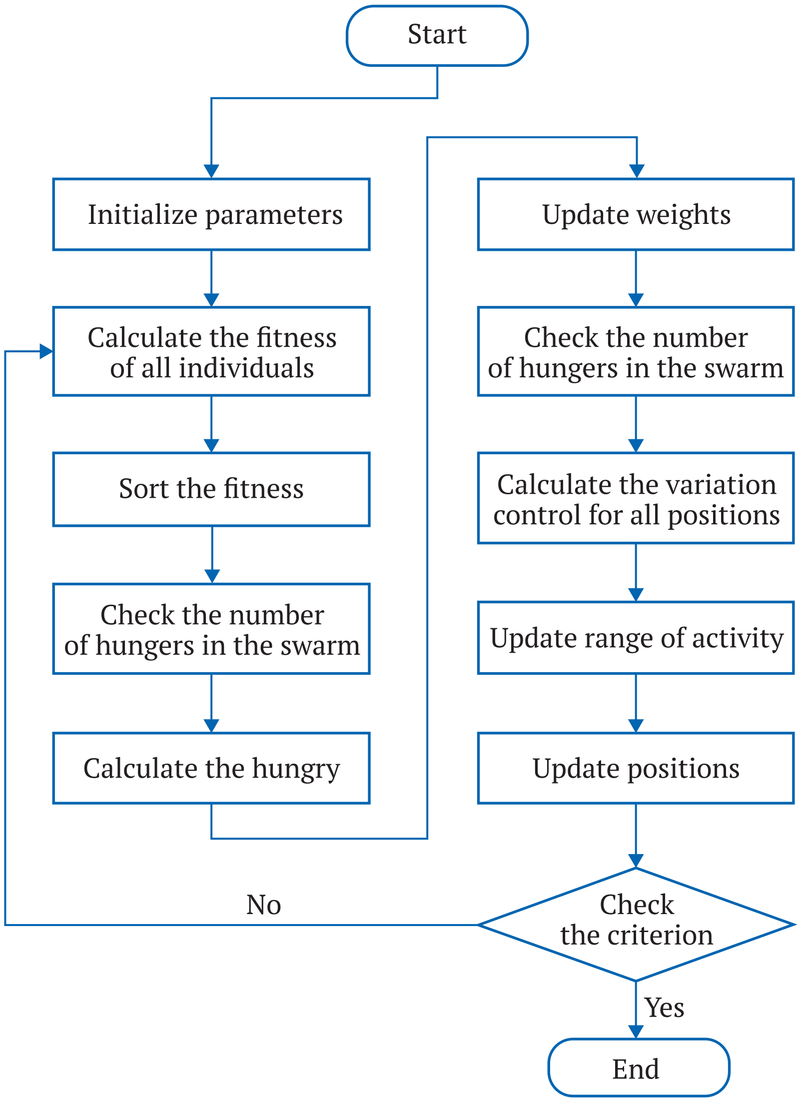

Fig. 5. HGS optimization algorithm simplified flowchart

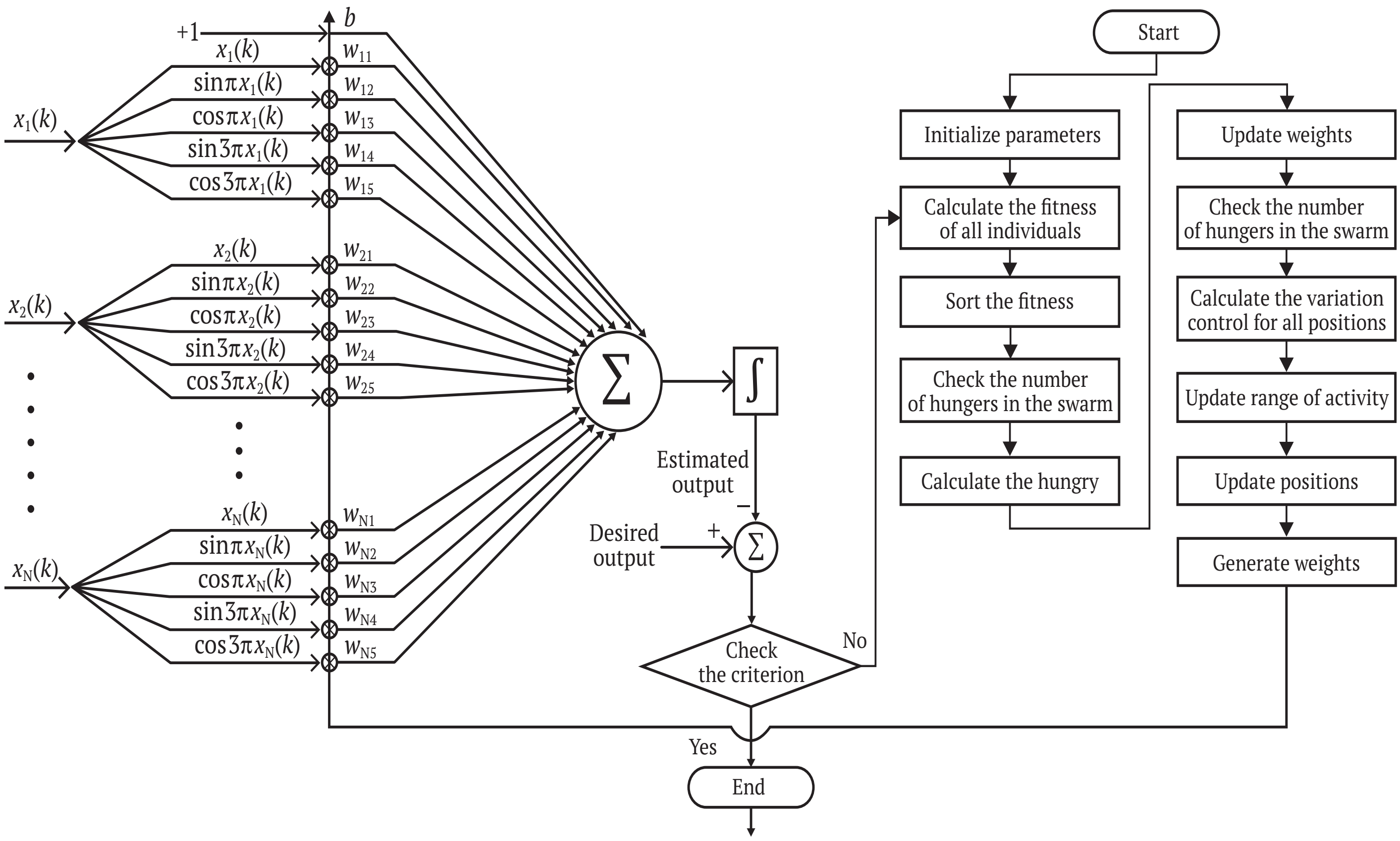

Fig. 6. Proposed HGS-FLNN model for predicting $PM_{2.5}$ in OPMs

Prior to optimizing the FLNN model, the functional expansion and HGS's parameters were established and calibrated. The Chebyshev function was selected as the FLNN model expansion function for transferring the input variables data (i.e., T, H, AP, WD, WS) to the hidden nodes. In addition, ReLu (Rectified Linear Unit) activation function was used to transform the data (weights) in the FLNN model nodes. For the HGS optimizer, different numbers of hungers were considered, e.g., 50, 100, 150, 200, 250, 300, 350, 400, 450, 500 for evaluating the optimizer performance. The switching updating position probability was selected equal to 0.03 with the threshold of 1000. For each hunger and its position, the HGS created weights and then updated them to the FLNN model. Finally, the RMSE values were calculated, and the best model with the lowest RMSE was selected, as shown in Figure 7. For this purpose, the Mealpy library developed by Thieu N.V.[2] was used. The performance curves show that the HGS-FLNN model training performance and RMSE are excellent. The next chapter is devoted to the performance testing and evaluation.

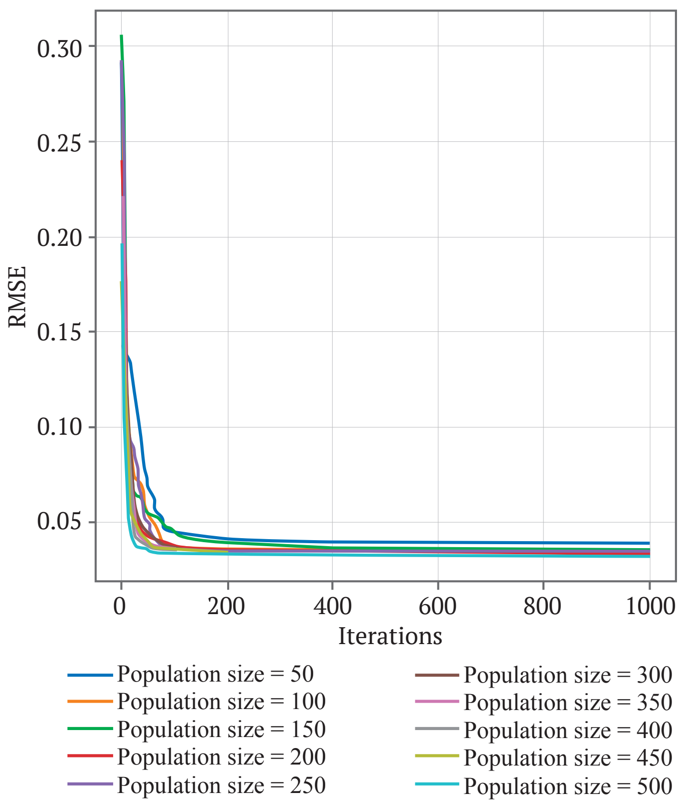

Fig. 7. Optimization performance of the HGS-FLNN model for predicting $PM_{2.5}$

[2] Thieu N.V. A collection of the state-of-the-art meta-heuristics algorithms in Python: Mealpy. 2020.

4. Development of other models for predicting $PM_{2.5}$

PSO, GA, and ABC well-known metaheuristic algorithms are widely used for resolving optimization problems [40–48]. In this study, we hybridized FLNN model (for predicting PM2.5 in OPCMs) with these algorithms to produce so-called PSO-FLNN, GA-FLNN, and ABC-FLNN models. It should be noted that they are also novel hybrid models related to air pollution prediction, especially for $PM_{2.5}$ predicting. The PSO, GA, and ABC basic principles are available in the following studies [49–61]. It is worth mentioning also that the role of the PSO, GA, and ABC is similar to the HGS optimizer in this study, and the development of the PSO-FLNN, GA-FLNN, and ABC-FLNN models is similar to that of the HGS-FLNN model.

4.1. PSO-FLNN

In order to develop the PSO-FLNN model, the same framework with Chebyshev function and ReLu activation function was used (similar to that used for the HGS-FLNN model). Different numbers of swarms were also set in interval of 50–500 similarly to those used for the HGS-FLNN model. The PSO's parameters were set as follows: C_1 = 1.2, C_2 = 1.2, W_{min} = 0.4, W_{max} = 0.9. The PSO was also implemented with 1000 iterations through RMSE objective function. The best PSO-FLNN model was then defined based on the lowest RMSE (Fig. 8).

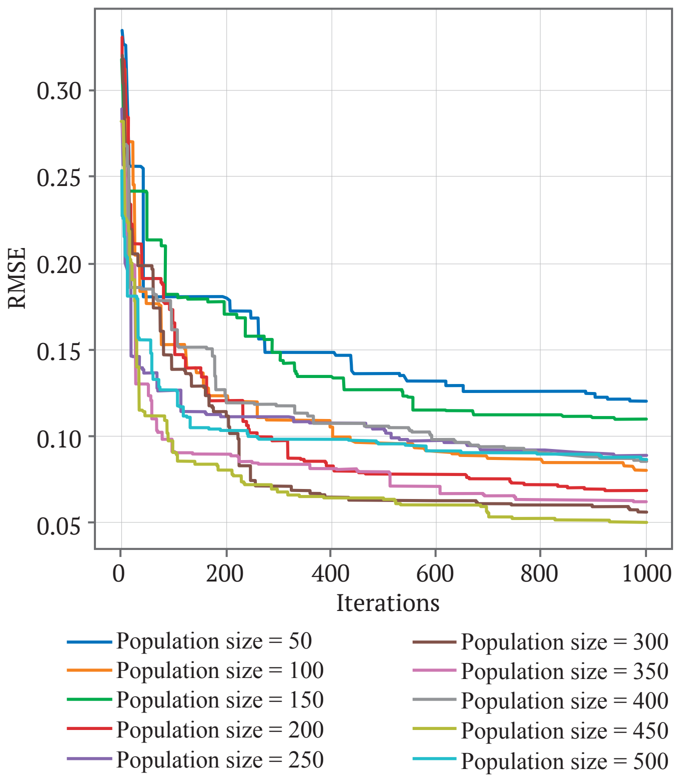

Fig. 8. Optimization performance of the PSO-FLNN model for predicting $PM_{2.5}$

4.2. GA-FLNN

In order to develop the GA-FLNN model, the same framework with Chebyshev function and ReLu activation function was used (similar to that used for the HGS-FLNN and PSO-FLNN models). Different numbers of swarms were also set in interval of 50–500 similarly to those used for the HGS-FLNN and PSO-FLNN models. The GA's parameters were set as follows: P_c = 0.85, P_m = 0.05. The GA was also implemented with 1000 iterations through RMSE objective function. The best GA-FLNN model was then defined based on the lowest RMSE (Fig. 9).

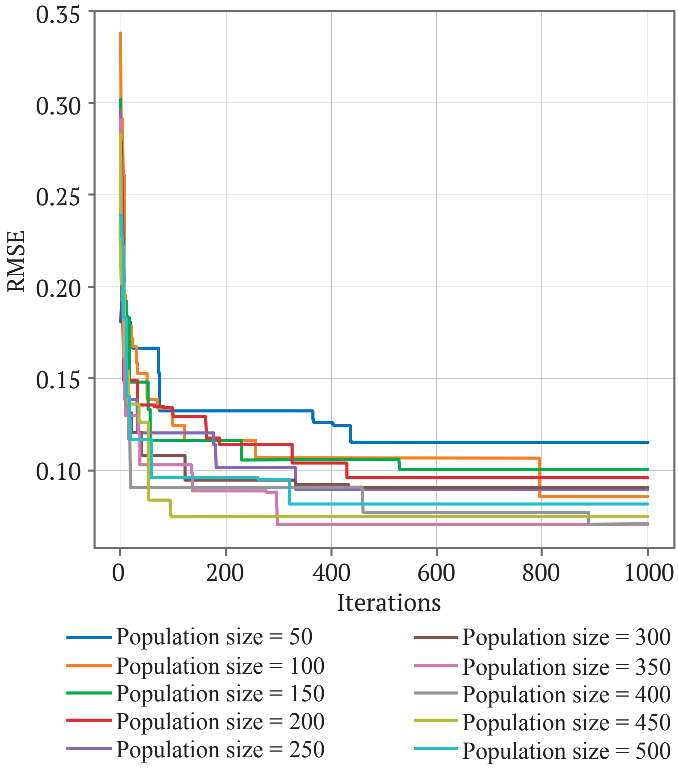

Fig. 9. Optimization performance of the GA-FLNN model for predicting $PM_{2.5}$

4.3. ABC-FLNN

Similar to the PSO-FLNN and GA-FLNN models, the ABC-FLNN model to predict $PM_{2.5}$ was also developed based on the same approaches. The same framework of the initial FLNN model (i.e. the inputs, expansion function, activation function) was used. Next, the ABC optimizer implemented global search to provide the set the number of weights. Subsequently, they were updated to the initial FLNN model and the error (i.e., RMSE) was calculated. Different numbers of bees were also set equal to 50–500, as those used for the HGS-FLNN, PSO-FLNN, and GA-FLNN models. The size of neighborhood for the elite and other bees (as the ABC's parameter) was set at 16.4. The ABC algorithm optimized the initial FLNN model with 1000 iterations through the RMSE objective function, as shown in Figure 10. Ultimately, the best ABC-FLNN model was defined based on the lowest RMSE. Training curves in Figure 10 show that the learning performance of the ABC-FLNN model is good. The next chapter describes the performance testing and evaluation.

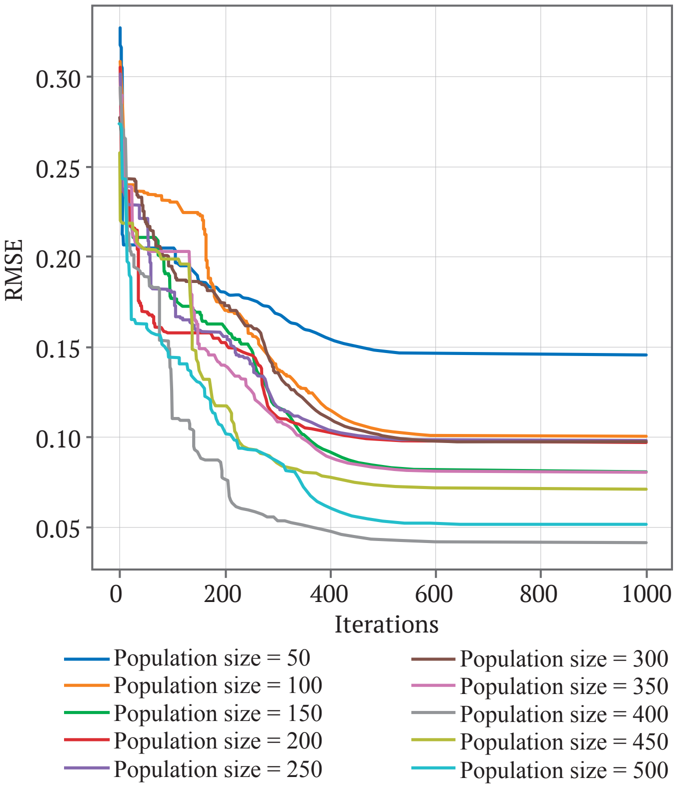

Fig. 10. Optimization performance of the ABC-FLNN model for predicting $PM_{2.5}$

5. Findings and discussion

Figures 5–8 demonstrate that the HGS-FLNN, ABC-FLNN, PSO-FLNN, and GA-FLNN models are well-trained with good convergence. However, it is difficult to indicate which model is the best for predicting $PM_{2.5}$ using these Figures only. We used statistical indices, such as MAE, RMSE, R^2, and MAPE to estimate the accuracy of the developed hybrid FLNN-based models. They are useful not only in estimating the accuracy of the models but also for determining the properties of the developed models (e.g., overfitting, underfitting). The results are presented in Table 2.

Table 2 shows that the HGS-FLNN model is obviously superior to the other models. In the HGS-FLNN model, the MAE ranges 1.405 to 1.497 only, whereas the ABC-FLNN, PSO-FLNN, and GA-FLNN models provided higher errors (MAE of 1.776, 2.326, 3.693, respectively, in the training dataset, and MAE of 2.246, 2.453, 3.602, respectively, in the testing dataset. Similarly to MAE, the RMSE values in the HGS-FLNN model amounting to 2.652 and 2.700 (in training and testing phases, respectively) are lower than those in other models. The training and testing phases of the other models yielded higher RMSE values (ranged 3.298–5.938 and 3.857–5.672, respectively). It is remarkable that MAPE was 0.054 only in the HGS-FLNN model training and 0.057 in testing of the corresponding dataset. In other words, the MAPE in the HGS-FLNN model-based predicting $PM_{2.5}$ ranged at 5.4–5.7 % only taking into account the meteorological conditions.

With regard to the level of regression in the models (i.e., correlation factor R^2), the results also indicated that the HGS-FLNN model demonstrated the highest R^2 in both phases. Furthermore, as observed, the developed models did not demonstrate overfitting. In other words, the training and testing phases showed practically similar accuracy of the results on predicting PM2.5 in this study. The visualization of the models regression levels in Figures 9 and 10 shows the best correlation between the predicted and measured data in the HGS-FLNN model, when compared to the other models. Whereas the correlation in the HGS-FLNN model is perfect, the other models (i.e., ABC-FLNN, PSO-FLNN, and GA-FLNN) demonstrate lower correlation, especially the GA-FLNN model. The GA-FLNN model demonstrated the lowest performance in predicting $PM_{2.5}$ in this study. The PSO-FLNN and ABC-FLNN models demonstrated better correlation/performance than the GA-FLNN model.

Turning to the FLNN-based models training performance (Figures 5–8), and taking a closer look at the performance lines and RMSE values, one can see that the HGS-FLNN model training performance is much better than that of the other models with lower RMSE values. This finding confirms the results presented in Table 2 and Figures 9–10. In other words, this con-

Table 2

Statistical indices for examination of the FLNN-based models for predicting $PM_{2.5}$

Model	Training				Testing			
	MAE	RMSE	R^2	MAPE	MAE	RMSE	R^2	MAPE
HGS-FLNN	1.405	2.652	0.967	0.054	1.497	2.700	0.966	0.057
ABC-FLNN	1.776	3.298	0.949	0.070	2.246	3.857	0.931	0.097
PSO-FLNN	2.326	3.968	0.930	0.087	2.453	3.962	0.933	0.091
GA-FLNN	3.693	5.938	0.837	0.125	3.602	5.672	0.852	0.129

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firms that the HGS algorithm performs better than the other algorithms (i.e., ABC, PSO, and GA) in this case. This statement does not mean that the HGS algorithm is better than the ABC, PSO, and GA algorithms in all cases. It depends on datasets used in each case study. Nevertheless, the HGS algorithm is considered as the best for predicting $PM_{2.5}$ in the OPCM at least in the present study. In order to measure the accuracy of the HGS-FLNN model in practice, the relative error (RE) was calculated, as shown in Figure 13. As can be seen, in the HGS-FLNN model, RE is very small. Most of the RE values ranges −0.3 to 0.5. Only one data point is out of this range, but this RE value is also low at 0.699. At the same time, the other models demonstrated higher REs, ranged −0.63 to 2.194. Notice that the ABC-FLNN model statistical indices (Table 2) indicated its better performance, when compared to the PSO-FLNN and GA-FLNN models. However, the ABC-FLNN model provided some data points with the highest RE, as shown in Figure 13. Finally, this study allowed a confident conclusion to be made that the HGS-FLNN model was the best technique to predict $PM_{2.5}$.

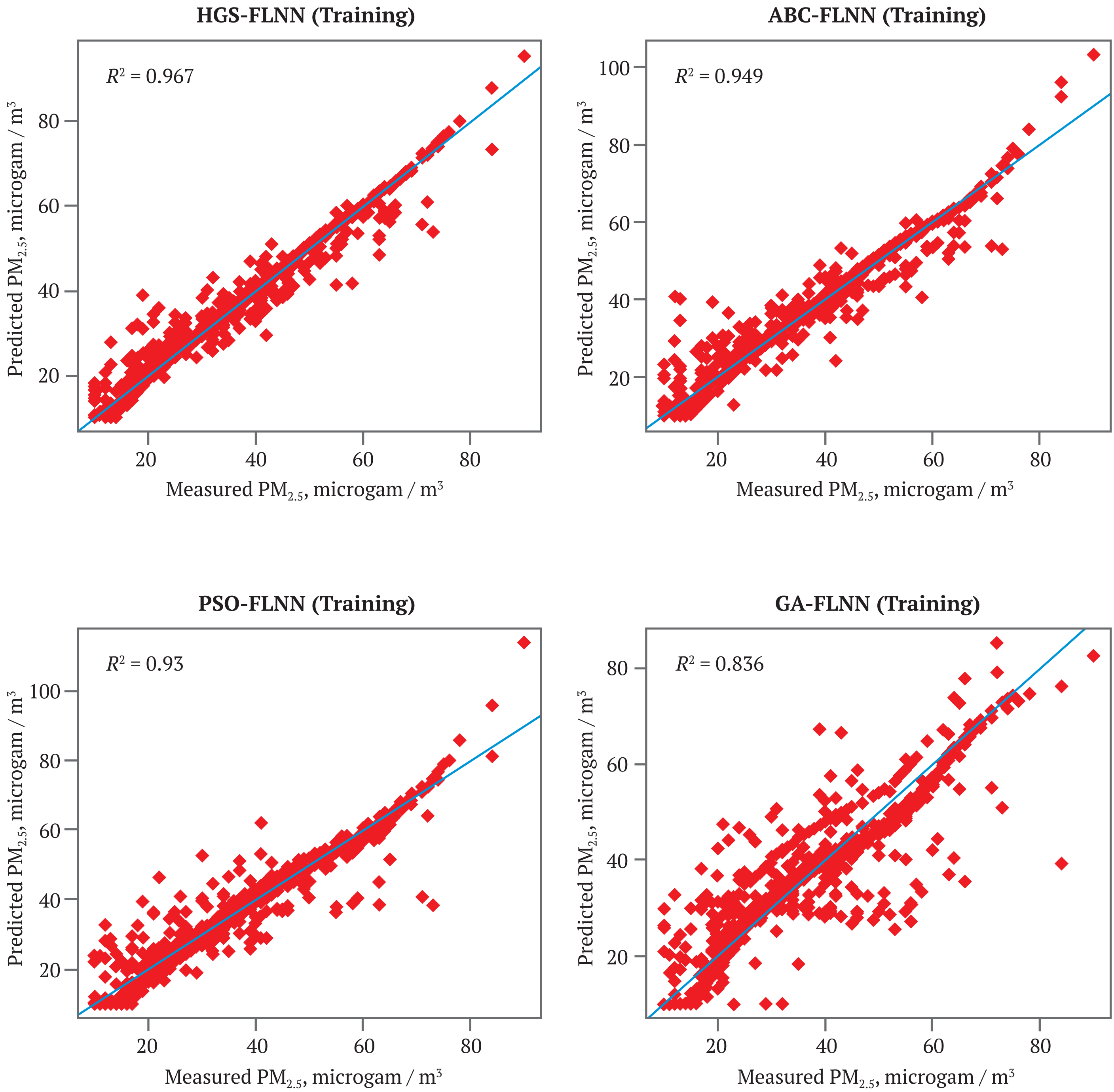

Fig. 11. Correlation between the predicted and measured data in the FLNN models (training dataset) under swarm-based algorithms optimization

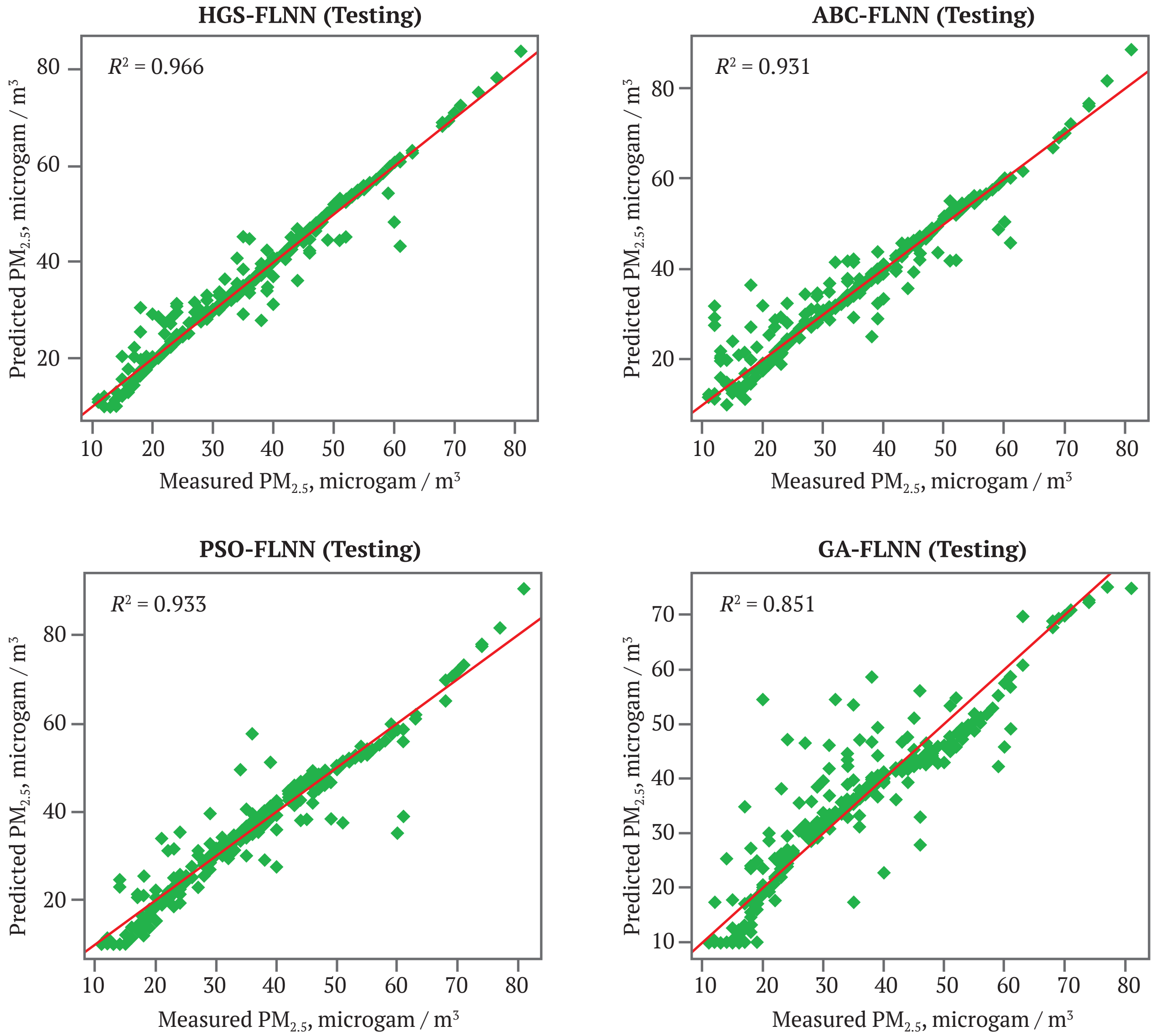

Fig. 12. Correlation between the predicted and measured data in the FLNN models (testing dataset) under swarm-based algorithms optimization

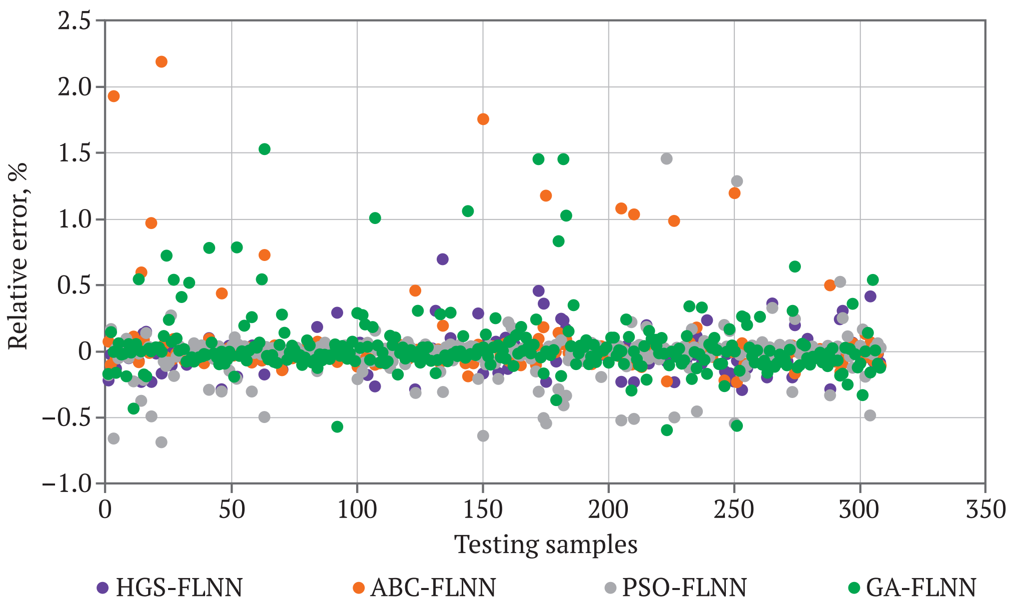

Fig. 13. Comparison of relative errors of the considered models

Conclusion

$PM_{2.5}$ in OPCMs is a serious occupational hazard to miners' health. It can cause respiratory, lung, cardiovascular, and cancer diseases. Historical reports indicate that increasing air PM2.5 pollution concentration by 10 μg/m³ results in an increase in lung cancer rate by 36 %. Meanwhile, OPCM $PM_{2.5}$ emissions measured in this study ranged 10 to 90 μg/m³. These are really hazardous levels for the health of miners. Therefore, accurate air $PM_{2.5}$ pollution prediction is of crucial importance in terms of occupational health and selecting solutions to reduce OPCM $PM_{2.5}$ pollution. This study proposed the novel HGS-FLNN model for predicting $PM_{2.5}$ pollution in OPCMs with an average accuracy of 94–95 %. In addition, three other hybrid models were developed, reviewed, and evaluated in terms of $PM_{2.5}$ prediction. However, their accuracy proved in the range of 87 % to 90 % only. The obtained results also indicated that the HGS-FLNN model was the most stable model with a very low relative error. It can be used in mining engineering to predict and control $PM_{2.5}$ pollution in OPCMs.

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