



Hybrid Metaheuristic-ANFIS Framework for Predicting and Inversely Optimizing Blast-Induced Flyrock: Social Spider and Salp Swarm Synergy

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Flyrock is one of the most serious consequences of surface mining and poses significant safety and operational risks. Traditional empirical models fail to capture the non-linear interactions between blasting parameters and rock mass properties, and most machine learning approaches only do forward prediction without providing design guidance. This paper introduces a new 2-phase hybrid framework that combines metaheuristic optimization with adaptive neuro-fuzzy inference system (ANFIS) modeling for both prediction and inverse blasting design. In the first phase, five state-of-the-art optimizers, including social spider optimization (SSpiderO), bird swarm algorithm (BSA), dragonfly optimization (DO), elephant herding optimization (EHO), and fireworks algorithm (FA), were used to tune ANFIS parameters. The results showed that the SSpiderO-ANFIS model was the most accurate and robust predictor of flyrock distance with accuracy of $\sim 82\%$; the other models only had 66–80% accuracy. In the second phase, salp swarm optimization (SSO) was applied to the trained SSpiderO-ANFIS model as a surrogate fitness function to inverse optimize blasting parameters under safety constraints. The results showed that the proposed framework not only outperformed traditional empirical and machine learning models in prediction but also provided optimized blasting configurations that restricted flyrock within regulatory limits. Sensitivity analysis also showed the relative effect of burden, spacing, stemming length and powder factor on flyrock behavior. The study demonstrates the practicality of combining prediction and optimization for safe and cost effective blast design and suggests future research on multi-objective optimization and transfer learning for broader applicability.

KEY WORDS: Flyrock prediction, Adaptive neuro-fuzzy inference system (ANFIS), Metaheuristic optimization, Social spider optimization (SSpiderO), Salp swarm optimization (SSO), Inverse blasting design, Surface mining safety.

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INTRODUCTION

Blasting is one of the most used techniques in surface mining and civil engineering projects due to its efficiency and cost effectiveness. However, blast induced hazards such as flyrock, ground vibration, air overpressure and dust emission compromise both operational safety and environmental sustainability (Sevelka 2024). Among these hazards, flyrock is the most critical and unpredictable (Hasanipanah and Bakhshandeh Amnieh 2020). Flyrock is the uncontrolled ejection of rock fragments beyond the blast zone, which can damage equipment, harm workers and even threaten nearby communities and infrastructures (Raina 2023; Sevelka 2024). Despite decades of research, predicting flyrock distance still remains a tough task due to the highly nonlinear and uncertain interactions between blasting design parameters, rock mass properties and geological conditions.

Traditional empirical equations and statistical regression models have been used to estimate flyrock distance (Ghasemi et al., 2012; Faramarzi et al., 2014). While these methods provide useful guidelines, they have limited generalization capability, as they are based on simplified assumptions and site specific data. Deterministic models fail to capture the complex nonlinear relationships among multiple blasting variables (e.g., burden, spacing, stemming length, charge weight, rock strength) and hence provide inaccurate predictions and reduced reliability in practical applications (Zhou et al., 2024). Therefore, mining engineers and researchers are increasingly exploring data-driven and intelligent methods that can model better the underlying patterns in blast performance.

Recent advancements in artificial intelligence (AI) and soft computing have shown great potential in solving complex engineering problems with high uncertainty (Liu et al., 2024; Wankhede et al., 2024; Zhang et al., 2025). Among them, adaptive neuro-fuzzy inference system (ANFIS) has been used widely as a powerful tool due to its ability to combine the learning capability of neural networks with the reasoning mechanism of fuzzy logic (Guerra et al., 2024). However, the performance of ANFIS highly depends on its parameter optimization, which is often trapped in local minima when conventional gradient based methods are used (Mhady et al., 2025). To overcome this issue, metaheuristic optimization algorithms have been increasingly used to fine-tune the ANFIS structure and parameters and

hence improve robustness and accuracy (Akiner and Ghasri 2024; Elsabagh et al., 2024; Somdutta and Rai 2025). Algorithms inspired by natural and swarm intelligence, such as social spider optimization (SSpiderO), bird swarm algorithm (BSA), dragonfly optimization (DO), elephant herding optimization (EHO), and fireworks algorithm (FA), have shown good results in various optimization problems but have not been explored yet in flyrock modeling (Meng et al., 2016; Tan 2019; Li et al., 2020a; Rahman et al., 2023; Abualigah et al., 2024). Despite these advancements, several critical research gaps still exist in the application of AI to mine blasting.

Indeed, most studies have focused on applying a single metaheuristic algorithm for training and optimizing the ANFIS model, without evaluating multiple strategies to determine the most effective optimizer. Second, while forward prediction of flyrock has been the main emphasis, inverse optimization, i.e., determining optimal blasting parameters to achieve safe flyrock distances has received limited attention. The inverse design perspective is particularly important for mine planners, as it shifts the modeling paradigm from merely predicting hazards to proactively controlling and mitigating them. To the best of our knowledge, no prior research has integrated a metaheuristic ensemble for ANFIS optimization with a subsequent inverse optimization stage for safe blast design.

Positioning against recent hybrid ANFIS models, recent studies have proposed several hybrid learning frameworks such as ANFIS-GOA, MSHHO-SVR, and boosted deep-kernel ensembles, which considerably improve forward predictive accuracy for flyrock. However, these approaches remain strictly forecast-oriented, providing no mechanism for translating predictions into safe and feasible blast-design parameters. Motivated by these gaps, this paper proposes a novel integrated metaheuristic-ANFIS framework for blast-induced flyrock prediction and control. This framework comprises a 2-phase predictive-prescriptive framework. First, 5 metaheuristics within a unified ANFIS architecture were benchmarked to obtain a robust surrogate model. Second, this robust surrogate was embed into a salp swarm-based inverse optimization module, thereby closing the loop from prediction to design by generating burden-spacing-stemming-PF configurations that satisfy regulatory flyrock limits. With these two phases (i.e., forward prediction and inverse optimization), this paper provides a state-of-

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the-art model in blast-induced flyrock modeling and a practical decision-support tool for safe blasting practices.

The contributions of this research are fourfold: (1) Development of hybrid metaheuristic-ANFIS models using five different optimizers, including SSpiderO, BSA, DO, EHO, and FA for accurate flyrock prediction. (2) Identification of the best-performing model, whereby the SSpiderO-ANFIS combination was selected as the most effective predictor. (3) Implementation of inverse optimization by employing the salp swarm optimization (SSO) algorithm to derive optimal blasting parameters corresponding to safe flyrock thresholds. (4) Application in practical engineering for blast design, assisting engineers in minimizing flyrock hazards and enhancing safety in blasting operations (Fig. 1).

LITERATURE REVIEW

Blast-Induced Flyrock Prediction Approaches

Flyrock has been known as one of the most hazardous outcomes of blasting operations resulting in serious safety incidents and economic losses. To control this phenomenon, various predictive methods have been proposed in the literature. Empirical formulas derived from site specific blasting data were the earliest attempts to estimate flyrock distance. These equations relate maximum charge per delay, burden or stemming length to the observed throw distance (Jahed Armaghani et al., 2016; Supandi 2024). Although simple and easy to apply, empirical models are highly site-dependent and often fail to generalize across different geological and operational conditions (Ghasemi et al., 2012; Szendrei and Tose 2022).

In parallel, statistical and regression based models were introduced to improve accuracy by incorporating multiple predictors simultaneously. Multivariate regression and analysis of variance (ANOVA) have been used to quantify the effect of explosive parameters and rock characteristics (Armaghani et al., 2016). While these models capture linear relationships well, they are often inadequate for modeling the nonlinear and stochastic nature of blasting dynamics (Mohamad et al., 2018).

In recent years, soft computing models based on artificial intelligence (AI) and machine learning (ML) have been applied widely in blast-induced flyrock prediction in open-pit mines (Marto et al.,

2014; Barkhordari et al., 2022a). Many models such as artificial neural network (ANN), support vector machine (SVM), random forest (RF) and hybrid models have shown better performance than traditional methods (Amini et al., 2012; Han et al., 2020; Wang et al., 2023). These models can explore and explain the complex hidden relationships between blasting parameters and geological conditions. However, their performance and accuracy are highly dependent on their structure, algorithms and optimization strategies. Thus, many researchers proposed hybrid models under the consideration of combining traditional AI/ML models with optimization algorithms (Al-Bakri and Sazid 2021; Li et al., 2023).

ANFIS in Mining and Blasting Problems

Among the diverse AI models introduced, ANFIS is one of the popular models that has been applied in mining and geotechnical engineering problems due to its hybrid nature. It combines the learning ability of neural networks with the interpretability of fuzzy inference systems. Hence, it is suitable for handling uncertainty and imprecision in blasting data.

In blasting applications, ANFIS has been used to predict outcomes such as blast-induced flyrock, blast-induced ground vibration, fragmentation size distribution and blast-induced air overpressure (Armaghani et al., 2015; Esmaeili et al., 2015; Trivedi et al., 2015; Hasanipanah et al., 2016b). These studies showed the flexibility and feasibility of ANFIS in modeling nonlinear relationships of multi-variables with limited data in open-pit mines. However, the training of ANFIS and optimization of hyperparameters (e.g., membership functions and fuzzy rules) is a big challenge (Yang et al., 2020). Traditional gradient descent algorithm or least-squares method may converge too early, reducing the predictive ability of ANFIS models (Karaboga and Kaya 2019). To overcome these limitations, researchers have proposed and applied metaheuristic algorithms to optimize ANFIS's structure and its parameters (Fattahi and Hasanipanah 2022).

Metaheuristic Algorithms in Blasting Operations

Metaheuristic algorithms, inspired by natural (i.e., swarm, math, bio, physics, human, system, etc.)

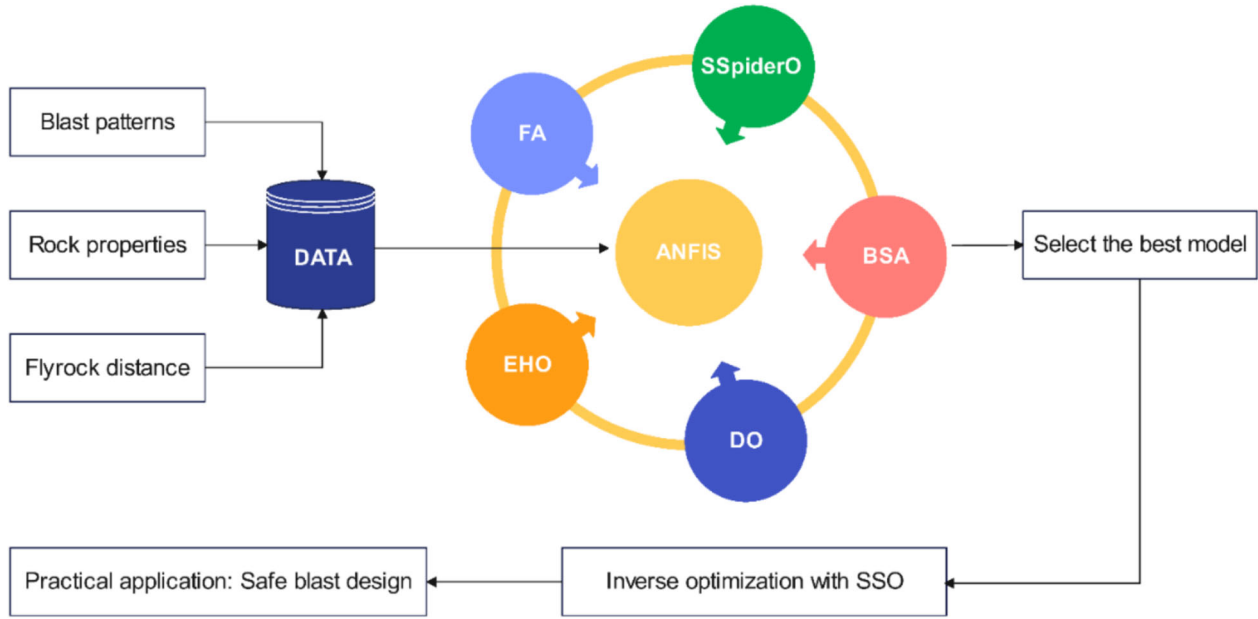


Figure 1. Workflow of proposed methodology.

and evolutionary processes, have been introduced as powerful tools for solving high-dimensional and nonlinear optimization problems. They offer flexibility, global search capability, and robustness against local optima. Popular families of metaheuristic algorithms include swarm intelligence algorithms (e.g., particle swarm optimization, ant colony optimization, SSO) and evolutionary strategies (e.g., genetic algorithms, differential evolution).

In mining and blasting, metaheuristics have been successfully used for: (a) blast parameter design optimization, aiming to balance fragmentation quality, flyrock control, and cost efficiency (Silveira and de Lima 2024); (b) hazard prediction models, where metaheuristics are integrated with ML or AI frameworks (e.g., GA-ANN, PSO-SVR) to enhance accuracy (Shylaja and Prashanth 2025); and (c) process simulation and inverse analysis, helping engineers determine optimal blasting setups for safe operations (Leon et al., 2025). Recent metaheuristics such as SSpiderO, BSA, DO, EHO, and FA have shown strong potential but are still rarely explored in blasting research (Darvishpoor et al., 2023; Subramanian et al., 2025). Their ability to explore complex search spaces makes them particularly suitable for training ANFIS models to achieve robust and accurate predictions.

Research Gaps

As mentioned earlier, despite these advancements, several critical research gaps still exist in the AI application of AI to mine blasting, including: (a) the application of a single metaheuristic algorithm for training and optimizing the ANFIS model, without evaluating multiple strategies to determine the most effective optimizer; (b) previous studies only mainly focused on the prediction of blast-induced flyrock, meanwhile the optimization of blasting parameters to control blast-induced flyrock is little attention; and (c) lack of integrated frameworks that combine metaheuristic algorithms not only for training and optimizing blast-induced flyrock but also for optimizing blasting parameters to reduce flyrock distance. This paper addresses these gaps by developing an integrated metaheuristic-ANFIS framework that employs multiple metaheuristics for predictive modeling and uses SSO for inverse design. Table 1 summarizes recent studies on flyrock prediction. Whereas the studies summarized in Table 1 rely exclusively on forward prediction, even when hybridized with advanced optimizers such as GOA, HHO variants, or boosted kernel architectures, the present work extends the scope of flyrock modeling by coupling a multi-optimizer surrogate learning stage with an inverse optimization

Table 1. Summary of recent studies on flyrock prediction

Study	Method(s)	Input variables	Output	Dataset	Performance (R^2 /RMSE)	Notes
Jahed Armaghani et al. (2015)	ANFIS	MC, PF	Flyrock	Quarry	$R^2 = 0.979$; RMSE = 0.029	Early ANFIS application
Stojadinović et al. (2015)	ANN	Db, TDh, Ss, SF, S, Trbv, PF, NR, B, Hb/B, Is/lbh, B/d, MC, Nb, Rn	Flyrock	Quarry	Accuracy ~ 94% ($\pm 10\%$)	Early ANN model with many inputs
Hasanipanah et al. (2016a)	PSO-Power Eq.	B, S, ST, PF, RD	Flyrock	Shur River Dam	$R^2 = 0.96$; RMSE = 12.01	PSO improved empirical power equation
Lu et al. (2019)	ORELM	B, S, ST, PF, RD	Flyrock	Quarry	RMSE = 12.75; MAE = 10.14	Robust ELM variant
Han et al. (2019)	Bayesian Network	Db, Dh, B/S, ST, MC, PF	Flyrock	Quarry	Probability ~ 100%	Probabilistic approach
Guo et al. (2019)	DNN	B, S, ST, PF, MC	Flyrock	Quarry	$R^2 = 0.978$; RMSE = 9.11	DNN with WOA optimization
Hasanipanah and Bakhshandeh Amnieh (2020)	GA-based	B, S, ST, Dh, RMR, Db, PF, Hb	Flyrock	Quarry	$R^2 = 0.984$; RMSE = 5.24	GA tuned fuzzy rules
Muridhar et al. (2020)	ELM-BBO	B/S, Db, PF, ST, MC, Dh	Flyrock	Quarry	$R^2 = 0.94$; RMSE = 18.84	Hybrid ELM with biogeography optimization
Armaghani et al. (2020)	SVR-GWO	Db, Dh, B/S, ST, MC, PF	Flyrock	Quarry	$R^2 = 0.905$; RMSE = 18.79	SVR with Grey Wolf Optimizer
Jamei et al. (2021)	KELM	B, S, ST, PF	Flyrock	Quarry	$R^2 = 0.971$; RMSE = 13.05	Kernel ELM approach
Muridhar et al. (2021)	HHO-MLP	Db, GSI, Dh, WI, ROD, ST/B, PF, CPM	Flyrock	Quarry	$R^2 = 0.996$; RMSE = 7.21	Harris Hawks + MLP
Monjezi et al. (2021)	GEP	B, S, ST, PF	Flyrock	Quarry	$R^2 = 0.91$; RMSE = 10.81	Gene Expression Programming
Dehghani et al. (2021)	GEP	S, B, ST, PF, Lc	Flyrock	Quarry	$R^2 = 0.914$	GEP with COA optimization
Fattahi and Hasanipanah (2021)	ANFIS-GOA	S, B, ST, PF, RD	Flyrock	Quarry	$R^2 = 0.974$; MSE = 0.003	Grasshopper-optimized ANFIS
Barkhordari et al. (2022b)	SSM-Bagging	Db, Dh, B/S, ST, MC, PF	Flyrock	Quarry	$R^2 = 0.974$; MSE = 0.0059	Ensemble bagging
Hudaverdi (2022)	ANFIS	B, S, Hb, Db, ST, Dsub, Te, Cs, Xbs, Mf	Flyrock	Quarry	$R = 0.986$; MAE = 5.4	Extended ANFIS with variable selection
Lawal et al. (2022)	ANN (UAV)	ST, MC, PF	Flyrock	Quarry	$R = 0.998$	UAV-based measurement
Li et al. (2023)	MSHMO-SVR	Db, Dh, B/S, ST, MC, PF	Flyrock	Quarry	$R^2 = 0.966$; RMSE = 12.28	Harris Hawks + SVR
Mishra et al. (2023)	ML (High-speed analysis)	Various blast parameters	Flyrock velocity & distance	Surface mines	$R^2 = 0.988$; RMSE = 0.87	Motion analysis-based ML
Chen et al. (2024)	PSO-MRA	Db, Dh, PF, ST, MC, B	Flyrock	Quarry	$R = 0.918$	Regression with PSO
Zhang et al. (2024)	Boosted SD-MKL	Dh, PF, ST, S, Ds, B	Flyrock	Quarry	RMSE = 1.73; VAF = 99.24	Boosted stacked deep kernels
Nguyen and Van Thieu (2025)	JADE-ANFIS	B, MEC, ST, PF	Flyrock	Copper mine	RMSE = 2.035; $R^2 = 0.978$	UAV + Proanalyst
Nguyen et al. (2025)	ANFIS-LJ	B, MEC, ST, PF	Flyrock	Copper mine	RMSE = 1.825; $R^2 = 0.988$	UAV + Proanalyst + Lévy-enhanced Jaya

stage. This design enables the proposed framework not only to forecast flyrock but also to derive actionable blast-design parameters that comply with a predetermined safety threshold.

METHODOLOGY

Dataset Description and Data Analysis

The dataset used in this study was compiled from 429 blasting operations at an open-pit mine, where detailed blast design parameters and geological indices were systematically recorded. The data included both design-related variables and rock mass characteristics, which together govern the extent of flyrock throw.

To develop an AI-based predictive model for blast-induced flyrock, the borehole diameter (d , mm), stemming-to-burden ratio (ST/B, $-$), explosive charge per borehole (C , kg); powder factor (PF, kg/m^3), blastability index (BI, $-$), and weathering index (WI, $-$) were considered as input variables, mainly to give a clearer picture of blast geometry, how explosive energy is distributed, and the basic mechanical behavior of the rock.

In this study, putting BI and WI together with the usual blasting parameters was a way to get a more “physical” sense of how flyrock actually forms during blasting. The traditional parameters (like B, ST, PF) mostly show how the explosive energy gets released, but the geological indices—especially WI—tell us more about how that energy moves through the rock mass, how it fades out, or gets redirected along weak zones. Once BI and WI are included, the models can sort of capture changes in block size, weathering, planes of weakness, and the overall fracture density a bit better. These aspects strongly affect fragmentation efficiency and the velocity of flyrock, even though they are often overlooked in simpler models. By using both sets of variables, the AI-based predictive models can reflect the design–geology interaction a bit better and, in turn, generalize across benches and lithologies more reliably than models relying only on blasting parameters.

The target output was flyrock distance (FR, m), defined as the horizontal distance between the blast face and the furthest ejected fragment. Field measurements were taken using GPS and then checked with high-resolution imaging. Table 2 provides the statistical summary of the dataset used here.

Table 2. Statistical summary of dataset

Feature (unit)	Min	Max	Mean	Standard deviation
d (mm)	76	150	94.821	21.121
ST/B ($-$)	0.23	2.28	0.984	0.466
C (Kg)	17	319	89.548	62.497
PF (Kg/m^3)	0.15	1	0.418	0.191
BI ($-$)	8	88	59.056	19.2
WI ($-$)	0.09	0.92	0.391	0.199
FR (m)	5	334	117.802	59.964

Before training the predictive models, the dataset was randomly split into training (70%) and testing (30%) subsets to keep the distributions roughly consistent. To reduce bias and improve robustness, a five-fold cross-validation procedure (repeated twice) was applied during the model training phase. Exploratory data analysis was done just to get a feel for the statistical characteristics and the sort of inter-relationships in the blasting dataset before moving on to model development. The whole point was basically to catch any quirks in the distributions, small anomalies that slip in, and to see how the inputs behave relative to the target output (flyrock distance, FR).

To avoid confusion later about how the models were evaluated, the data-partitioning and validation workflow is laid out here. The 70/30 training/testing split was applied once and then kept as-is for all the hybrid ANFIS-metaheuristic models, mostly to keep the comparison fair. With the 70% training subset, a repeated 5-fold cross-validation setup (five folds $\times$ two repeats) was used to tune the ANFIS parameters during the metaheuristic search. It turned out that this setup gave a more stable sense of generalization and made the results a bit less tied to, how the folds happened to fall.

The performance metrics in Table 5 refer to the testing subset results after each optimized model was trained using that same fixed split, while the cross-validation outcomes were only used for guiding the optimization, not for the final reporting. Keeping things separate like this helps to ensure that comparisons across metaheuristics actually reflect unseen data, and it also helps with reproducibility even if the workflow feels a bit rigid.

Histograms in Figure 2 were produced for all explanatory variables, including hole diameter (d), stemming-to-burden ratio (ST/B), explosive charge per hole (C), powder factor (PF), blastability index (BI), and weathering index (WI). The plots show

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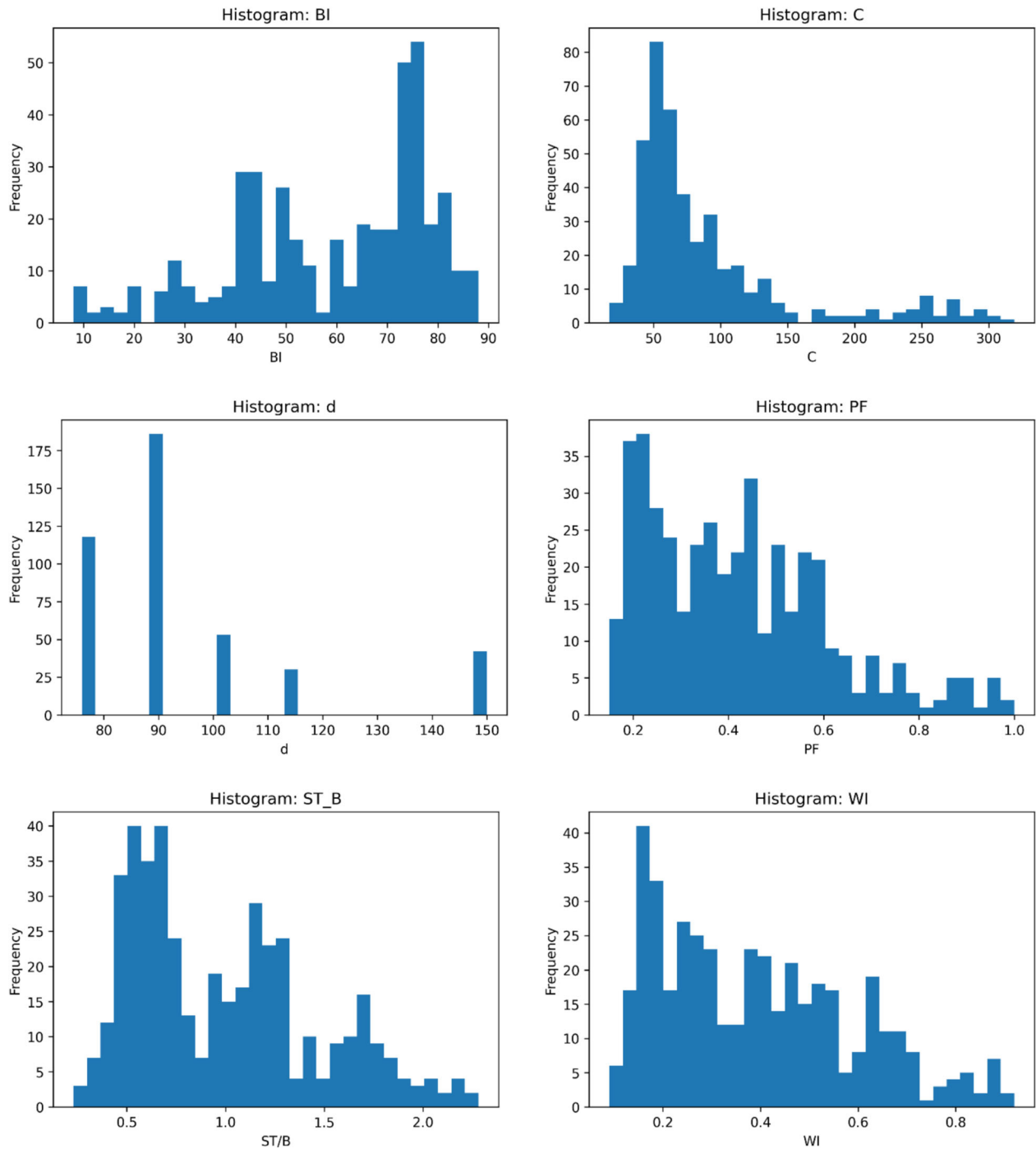


Figure 2. Distribution histograms of blasting and rock parameters.

that some variables, especially C and PF, are right-skewed, meaning there are a few fairly large charge values. BI looks multimodal, which basically just mirrors the mixed rock-mass conditions across sites.

WI, on the other hand, is strongly left-skewed with most samples packed in the lower weathering range (roughly 0.1–0.4), maybe a bit more than one might expect at first glance.

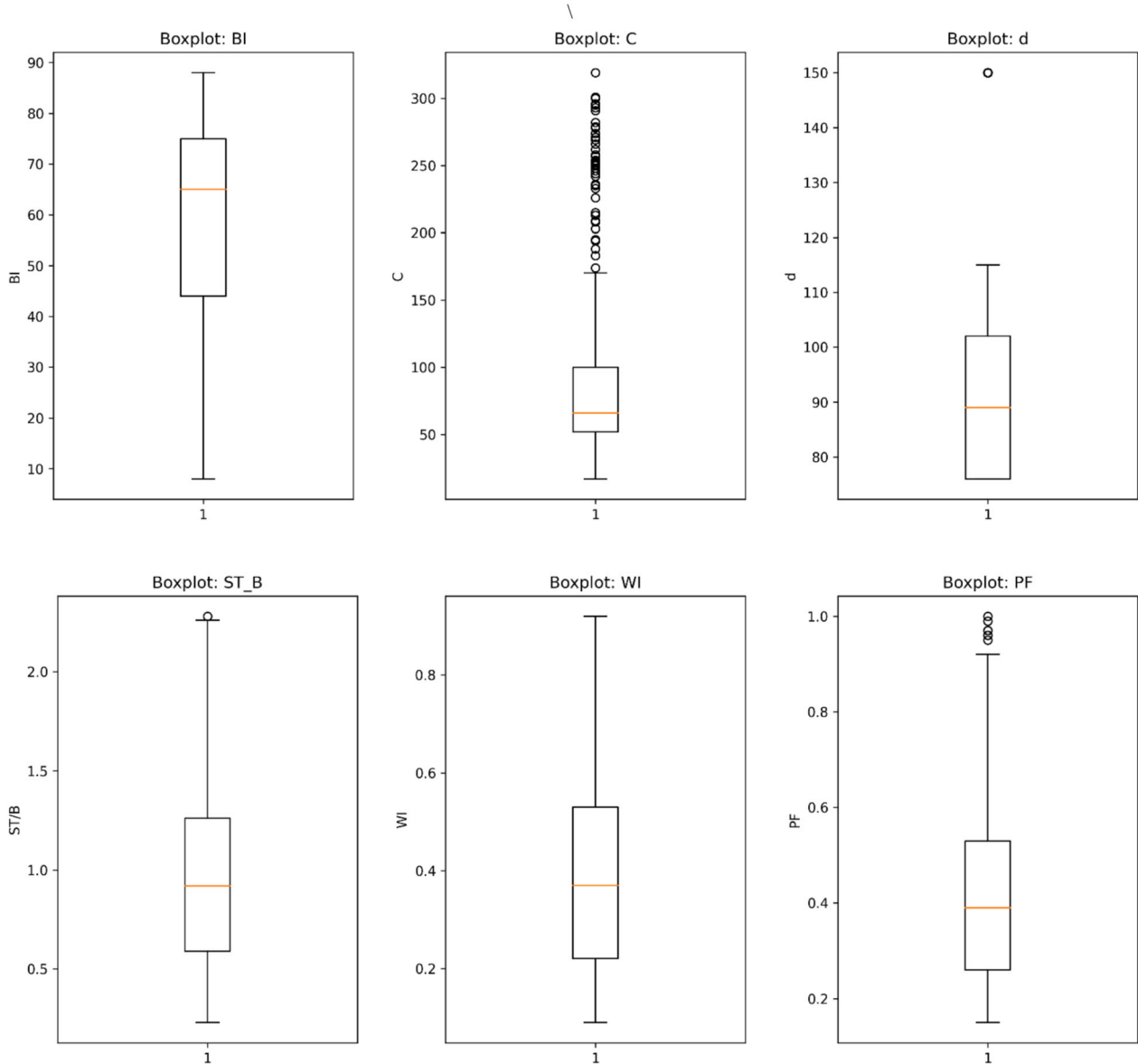


Figure 3. Boxplots of all input variables.

Boxplots in Figure 3 were checked to see if any extreme observations popped up. Outliers showed up most clearly in C and PF, which actually matched what the skewed histograms already hinted at. These points tie back to extreme blasting conditions (like very high charge per hole or a high powder factor) and, if they're just removed without thinking, they might twist how the predictive model picks up the underlying patterns. A few minor outliers also showed up in ST/B and d. Since these values reflect

actual operational scenarios rather than measurement issues, they were kept for the modeling phase.

To assess how the variables depend on each other, a Spearman's rank correlation heatmap was created (Fig. 4). The main patterns are fairly clear, even if the correlations don't line up perfectly across all samples.

The correlation analysis in Figure 4 shows a few variables linking to FR quite strongly. PF and WI have the highest positive correlations with FR, and d also shows a noticeable positive link. BI, in contrast,

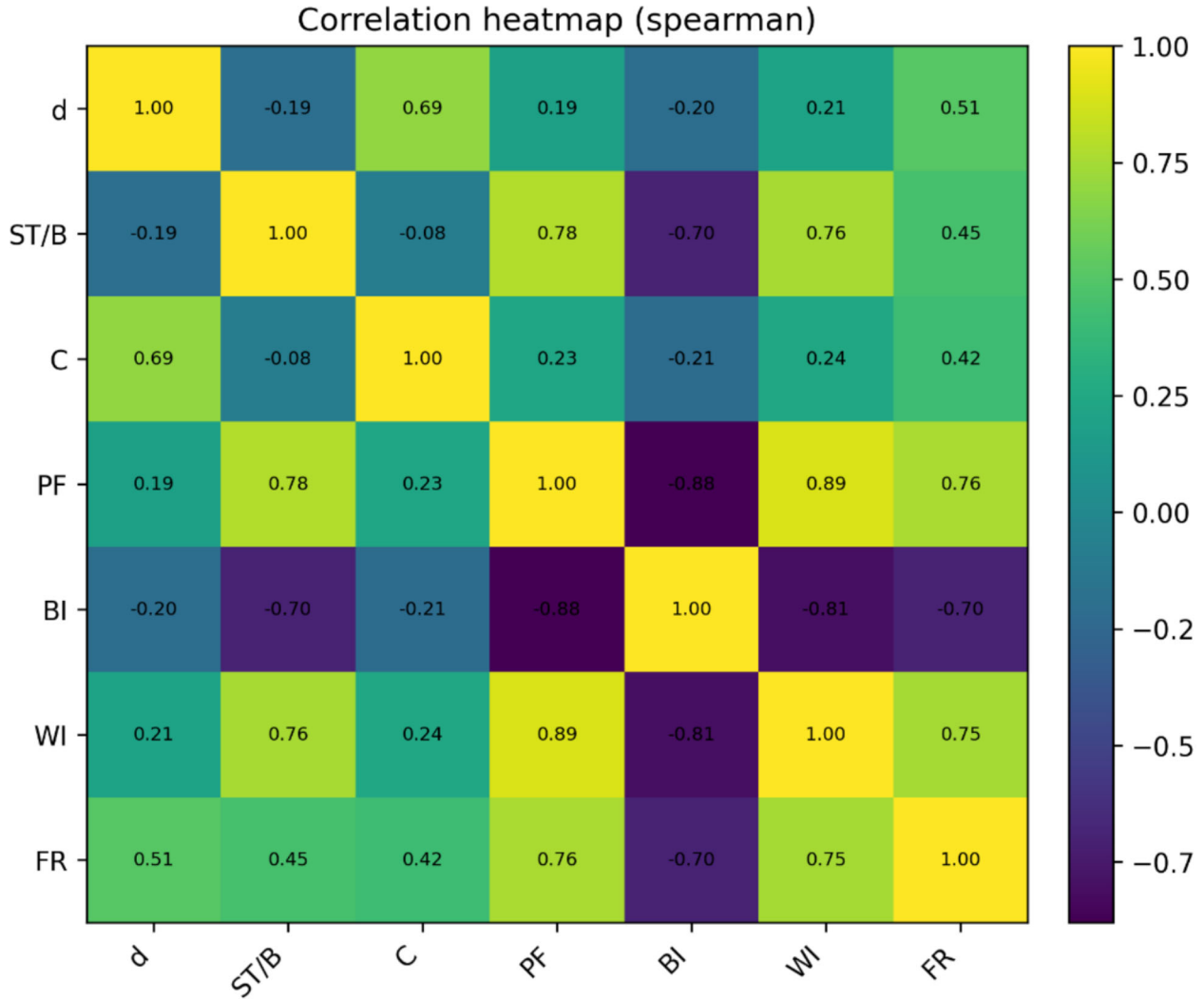


Figure 4. Spearman correlation heatmap of blasting parameters and flyrock.

is strongly negative. These patterns match basic blasting behavior: higher explosive energy (PF), more weathering (WI), and larger geometry effects through d often push flyrock farther, while higher BI tends to mark stronger rock that throws less material.

The dataset itself is not very clean in terms of distribution. Many variables are skewed, and some outliers appear, although they reflect real operating conditions instead of measurement mistakes. Moderate-to-strong correlations also exist among PF, ST/B, WI, and BI. Such multicollinearity can cause instability in simple linear models, but ANFIS deals with it better because of its non-linear mem-

bership functions and the rule-based structure, so the effect is reduced.

All six predictors were still kept. Each one represents a different physical part of the blasting process: confinement and geometry (d, ST/B), explosive energy and its spread (C, PF), and the geological-weathering condition (BI, WI). Removing any predictor would make the model less clear in meaning and less suitable for practical design work. Keeping the full input set also ensures compatibility with the SSO-based inverse design step, where candidate blast settings must map into all six inputs of the surrogate. For these reasons, the full set was preserved to capture the main physical factors behind flyrock behavior.

ANFIS Model Architecture

ANFIS is a hybrid soft-computing method that mixes the human-like reasoning of a fuzzy inference system with the adaptive learning part of a neural network. This combination lets ANFIS handle nonlinear functions fairly well, even when the relationships are not clean or smooth. Because of that, the method fits complex engineering tasks, including predicting blast-induced flyrock, where many variables interact in ways that are not easy to model directly. The ANFIS framework is constructed on the foundation of Takagi–Sugeno fuzzy inference rules, which are expressed in the general form:

Rule i : If x_1 is A_{1i} and x_2 is A_{2i} and ... and x_n is A_{ni} , then $y_i = p_0 + p_1x_1 + p_2x_2 + \dots + p_nx_n$

where $x_1, x_2, \dots, x_n$ are input variables, A_{ki} represents the fuzzy set associated with the k^{th} input in the i^{th} rule, and $p_0, p_1, \dots, p_n$ are the linear consequent parameters. By combining multiple rules, ANFIS creates a nonlinear mapping between blast parameters and flyrock distance.

Each input parameter is fuzzified into several membership functions (MFs), which define the degree to which a variable belongs to a particular fuzzy set (e.g., *low*, *medium*, *high*). In this study, generalized bell-shaped functions were employed due to their flexibility and smoothness, thus:

$$\mu(x; c, a, b) = \frac{1}{1 + \left| \frac{x-c}{a} \right|^{2b}} \quad (1)$$

where c is the center, a controls the width, and b determines the slope. The optimal parameters of the MFs were tuned using metaheuristic algorithms to maximize predictive accuracy.

The fuzzy rule base is then generated automatically by combining input MFs. For example with 3 inputs each with 3 MFs the system generates $3^3 = 27$ rules. While this gives high flexibility it also increases the risk of overfitting; hence metaheuristic optimization plays a big role in balancing accuracy and generalization. Figure 5 interprets the structure of ANFIS model in this study.

ANFIS uses a hybrid 2-stage learning approach for the learning mechanism: (1) forward pass: estimation of output parameters using least squares; (2) backward pass: adjustment of MF parameters using gradient descent (further optimized by metaheuristics in this study). This 2-stage learning enables ANFIS to iteratively refine both premise (MF) and consequent (linear output) parameters and get an

accurate nonlinear mapping between blast design variables and flyrock distance.

To ensure full reproducibility, the ANFIS surrogate used in this study was implemented with a well-defined and fixed internal structure prior to metaheuristic training. Each of the six input variables was assigned two Gaussian membership functions (MFs), selected for their smooth differentiability and stable optimization behavior. This results in 12 antecedent MFs in total. The rule base follows a first-order Takagi–Sugeno formulation with linear consequents, and the hybrid learning algorithm combines least-squares estimation for the consequent parameters with gradient-based tuning of MF parameters. The output layer uses a weighted average defuzzification scheme. All metaheuristics (GA, GWO, ACO, ABC, and SSpiderO) optimize only the MF parameters and consequent coefficients while keeping the structural configuration (number of MFs, MF type, and rule formulation) fixed. This explicit specification provides a fully reproducible ANFIS architecture for future benchmarking studies.

Phase I: Metaheuristic-ANFIS for Prediction

Five different metaheuristic algorithms were used to optimize the membership function and rule parameters of ANFIS to improve its prediction performance. Each algorithm was chosen for its balance between exploration and exploitation and for its success in solving complex engineering problems. The combination of these optimizers with ANFIS prevents the premature convergence that occurs with traditional gradient-based methods.

Social Spider Optimization (SSpiderO)

SSpiderO takes its idea from how social spiders forage and sort of “talk” to each other through web vibrations (Luque-Chang et al., 2018). In this setup, each solution behaves like a spider on a shared web and sends out vibrations depending on how good its fitness is (Nguyen 2019). Other spiders then shift their positions based on stronger vibrations, so information spreads across the whole group (Abualigah et al., 2024). This social mechanism gives SSpiderO a workable balance between global searching and local fine-tuning, which turns out to be

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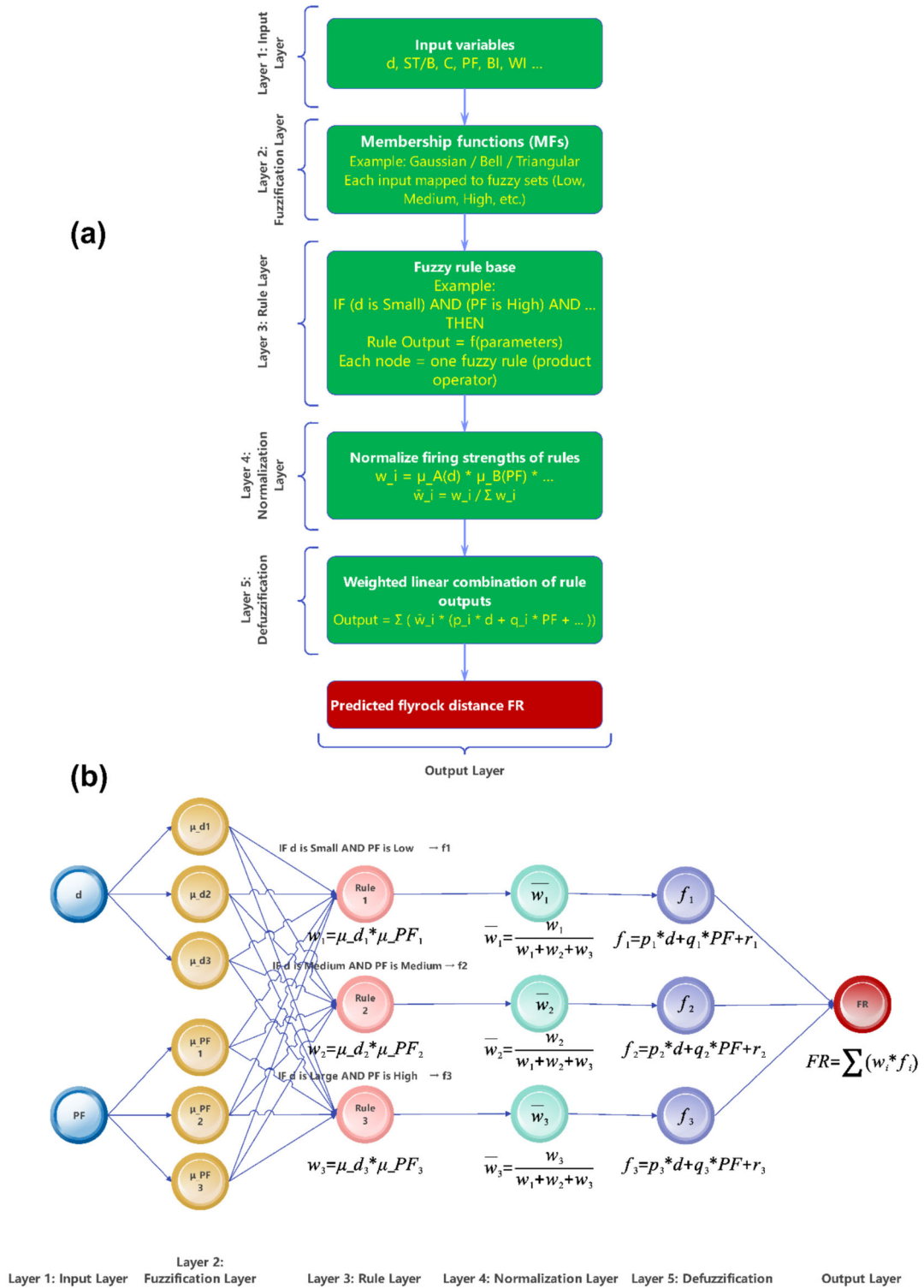


Figure 5. ANFIS structure with input variables: (a) general structure of ANFIS; (b) an example of ANFIS with 2 input variables.

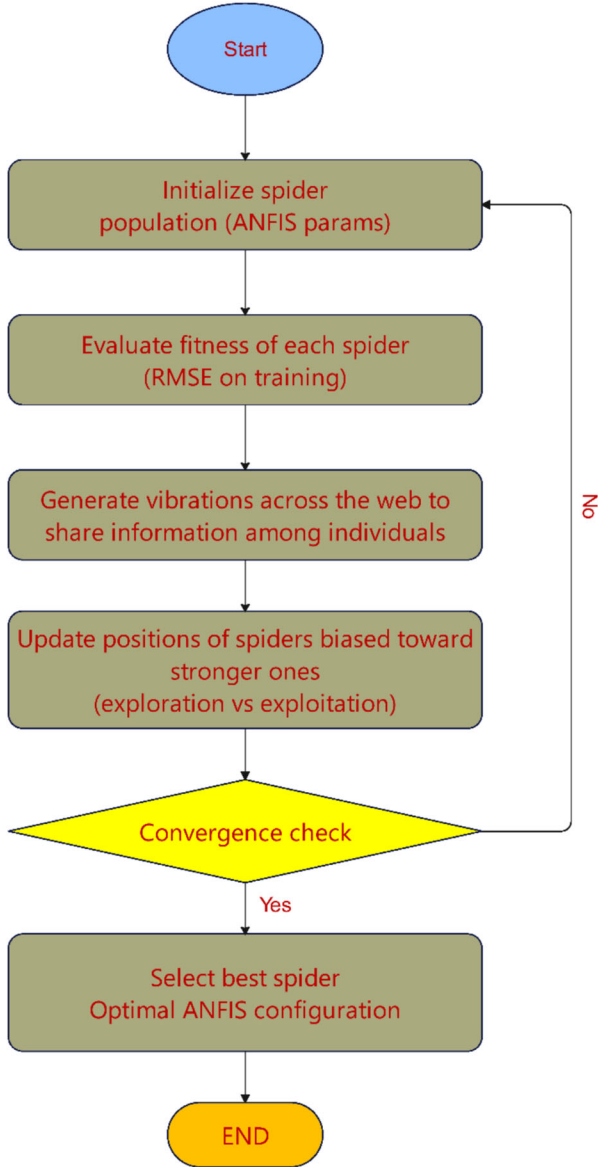


Figure 6. Flowchart of social spider optimization.

helpful for nonlinear problems like predicting fly-rock.

Bird Swarm Algorithm (BSA)

BSA follows the basic idea of bird groups that switch between foraging and vigilance behaviors (Varol Altay & Alatas 2020). Birds move in foraging mode when searching new areas and shift to vigilance mode to share cues or avoid risks (Parashar et al., 2017). With this switching pattern, BSA avoids getting stuck at local optima and still converges fairly quickly (Mesquita & Gaspar 2021). In ANFIS tuning, BSA adjusts MF parameters by supporting wide exploration first and then more focused exploitation.

Dragonfly Optimization (DO)

DO is inspired by how dragonflies swarm using five basic behaviors: alignment, separation, cohesion, moving toward food, and steering away from enemies (Emambocus et al., 2021). These five moves help DO juggle exploration and exploitation in a fairly natural way (Rahman and Rashid 2019). Applied to ANFIS tuning, DO gradually nudges the population toward better fuzzy-rule configurations by combining these cooperative actions.

Elephant Herding Optimization (EHO)

EHO mimics the clan structure of elephants, where individuals usually follow a matriarch, while a few split off to roam outside (Li et al., 2020b). The clan-update step keeps the search tight and exploitative inside the group, while the separating

Table 3. Parameter settings of five metaheuristics

Algorithm	Population size	Max iterations	Key parameters	Values
SSpiderO	50–300	1000	Attenuation rate (r), vibration constant (v)	$r = 0.5$, $v = 1.0$
BSA	50–300	1000	Foraging probability (p), vigilance coefficient (β)	$p = 0.8$, $\beta = 1.5$
DO	50–300	1000	Alignment (w_1), cohesion (w_2), separation (w_3)	$w_1 = 0.1$, $w_2 = 0.1$, $w_3 = 0.1$
EHO	50–300	1000	Clan size, separation probability	Clan = 5, $p = 0.3$
FA	50–300	1000	Explosion amplitude (A), spark number (S)	$A = 40$, $S = 50$

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step adds diversity (Ismaeel et al., 2019). Because of this simple two-part mechanism, EHO works quite well in practice for adjusting ANFIS parameters.

Fireworks Algorithm (FA)

FA imitates how fireworks explode and create sparks around each candidate solution (Ehsaeyan & Zolghadrasli 2022). The number and spread of sparks depend on the fitness of the solution, so promising regions get more detailed search while exploration is still maintained (Tan & Zhu 2010). The random spark process also improves global searching, which helps avoid local minima during ANFIS training.

Convergence Process

For all 5 optimizers, the convergence criterion was defined by either reaching the maximum number of iterations (1000 generations) or achieving a negligible improvement in the objective function. The objective function was the minimization of the root mean square error (RMSE) between predicted and observed flyrock distances on the training dataset.

At each iteration, candidate solutions (sets of ANFIS parameters) were evaluated based on RMSE. The optimizers updated their populations using their respective operators until the convergence criterion was satisfied. The best-performing ANFIS model was then selected for subsequent analysis. Figure 6 shows the flowchart of social spider optimization and the parameter settings of the five metaheuristics are presented in Table 3.

It should be noted that, in this study, population size was not fixed in advance but incorporated as a hyperparameter of the metaheuristic optimizers. To systematically assess its influence on convergence behavior, each algorithm was executed using six population sizes: 50, 100, 150, 200, 250, and 300. These configurations were evaluated under the same repeated 5-fold cross-validation setup and across 20 independent stochastic runs to keep the results stable.

The final population size listed for each metaheuristic is the one that gave the best predictive accuracy after cross-validation. Treating population size as a tunable hyperparameter helps keep the

comparison fair and avoids bias from fixing this parameter without a clear reason.

Phase II: Inverse Optimization with SSO

Accurate flyrock prediction is definitely useful for hazard assessment, but in practice the more meaningful goal is figuring out blasting settings that actually keep flyrock within safe limits. For that part, the best predictive model—SSpiderO-ANFIS—was treated as a kind of surrogate loss function. Then the model was dropped into an inverse-design setup driven by the SSO algorithm.

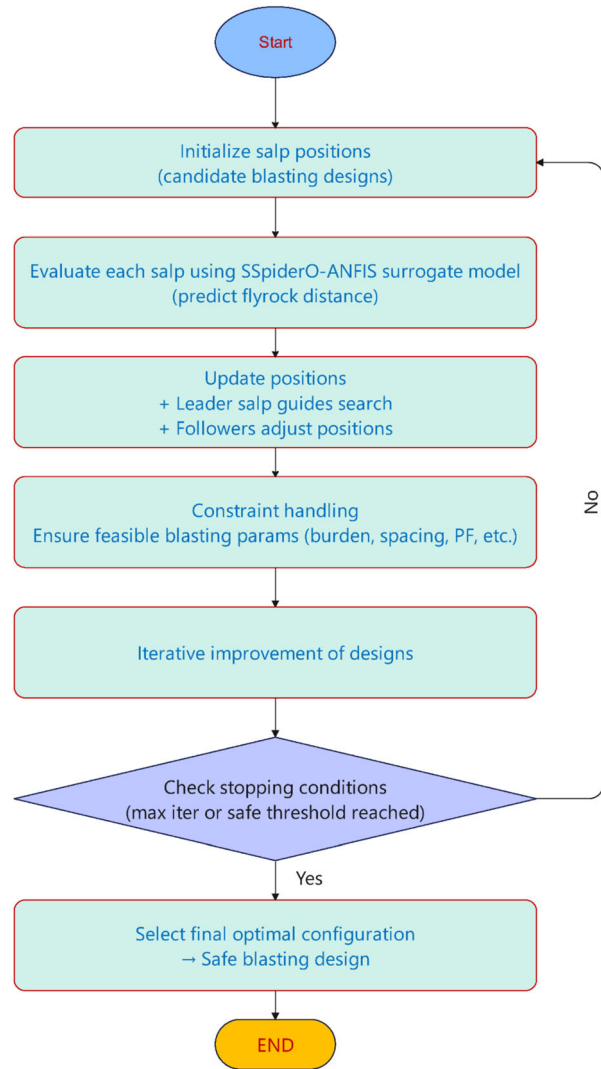


Figure 7. Flowchart of salp swarm optimization for inverse blasting design.

Table 4. Decision variables and constraints for inverse optimization using SSO

Variable	Unit	Lower bound	Upper bound	Constraint/Note
Burden (B)	m	2.5	5.0	Must ensure stable burden–spacing ratio
Spacing (S)	m	2.5	6.0	Typically $1.0\text{--}1.5 \times$ burden
Stemming (ST)	m	1.5	4.0	Minimum 20–25% of hole depth
Charge per hole (C)	kg	50	250	Limited by safety and explosive license
Powder factor (PF)	kg/m ³	0.3	1.0	Must meet fragmentation requirements
Bench height (H)	m	8	15	Mine design constraint
Hole diameter (D)	mm	76	115	Limited by drilling equipment
Rock hardness (H_r)	–	4	8	Geological index (fixed per site)
Flyrock distance (D_{FR})	m	–	≤ 300	Safety threshold requirement

SSO itself comes from the chain-like foraging motion of salps in the ocean. It handles multi-dimensional search spaces well and usually avoids getting stuck in local optima, which makes it a decent fit for this sort of inverse optimization task. By combining SSO with the surrogate model, blasting parameters can be iteratively optimized to minimize flyrock distance or keep it below a safety threshold. This two phase approach not only predicts hazards but also gives actionable guidance for safe blasting. The inverse optimization problem was formulated as follows:

Objective function:

$$\min f(x) = |D\hat{F}R(x) - DFR_{\text{target}}| \quad (2)$$

where $D\hat{F}R(x)$ is the predicted flyrock distance by SSpiderO-ANFIS given blasting inputs x , and DFR_{target} is the predefined safety limit.

Decision variables: blasting parameters controllable by engineers (e.g., burden, spacing, stemming, charge).

Constraints: operational and safety limits such as maximum explosive charge per hole, minimum stemming length, and allowable ranges for burden and spacing.

SSO operators:

- Leader update: guides the swarm toward the global best solution.
- Follower update: maintains diversity and ensures exploration.
- Convergence: achieved when maximum iterations are reached (1000) or when the predicted flyrock remains consistently below the threshold.

Figure 7 interprets the flowchart of the SSO for inverse blasting design for minimizing flyrock distance based on the best developed AI model in the previous step. Table 4 listed the decision variables and constraints for inverse optimization using SSO.

Although several metaheuristics could be employed for the inverse optimization stage, SSO offers structural characteristics that make it particularly suitable for blast-parameter design. First, SSO has a remarkably simple formulation with only one main control parameter, which reduces the risk of hyper-parameter sensitivity and makes the search behavior highly stable for constrained, low-dimensional optimization tasks. Second, the contraction-based movement of the salp chain naturally drives the population toward feasible regions of the design space, which is advantageous when optimizing parameters that must strictly satisfy safety limits on flyrock distance. Third, in contrast to SSpiderO or BSA, which are highly effective for high-dimensional surrogate training but may exhibit slower contraction in narrow feasible manifolds, SSO converges rapidly once promising regions are identified. The complementarity between SSpiderO (explorative surrogate training) and SSO (efficient constraint-respecting inverse search) provides a balanced two-stage workflow for predictive–prescriptive blast design.

In this study, the predictive (forward) and prescriptive (inverse) tasks play fundamentally different roles. The forward problem consists of learning the mapping (design variables, geological properties, and flyrock distance) using the metaheuristic-ANFIS models. In contrast, the inverse problem seeks (design variables aiming to satisfying a predefined flyrock safety limit) and therefore requires searching within a constrained subset of the design space. Because flyrock is not analytically invertible with respect to burden, spacing, stemming, and powder factor, the trained metaheuristic-ANFIS model functions as a surrogate bridge: it provides fast, differentiable-free evaluations of candidate solutions, allowing the SSO optimizer to navigate the

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inverse problem efficiently. This conceptual separation clarifies the 2-phase workflow and highlights why the surrogate model is essential for transforming an otherwise intractable inverse design task into a tractable optimization problem.

To make the inverse-design formulation explicit, the SSO optimizer minimizes a soft-constrained objective function rather than a pure unconstrained flyrock minimization. The optimization seeks to reduce the predicted flyrock distance $\hat{F}\hat{R}$ while ensuring compliance with the safety limit of 300 m. This is implemented through a penalty-augmented objective of the form:

$$\text{Objective} = \hat{F}\hat{R} + \lambda \cdot \max(0, \hat{F}\hat{R} - 300) \quad (3)$$

where λ is a penalty coefficient chosen to strongly discourage solutions violating the safety threshold. When $\hat{F}\hat{R} \leq 300$ m, the penalty term basically drops out, so the search just behaves like a normal minimization of $\hat{F}\hat{R}$ inside the feasible region. But when $\hat{F}\hat{R} > 300$ m, the penalty grows more or less linearly, nudging the optimizer back toward safer blasting setups. This setup keeps the convergence smooth, avoids weird jumps in the search space, and makes the behavior across candidate solutions a lot more consistent.

During the inverse optimization stage, the feasibility of the candidate blasting configurations is kept through a sort of two-layer constraint-handling approach. First, SSO enforces bound constraints with a simple repair step: whenever an updated position goes outside the allowed physical limits (e.g., burden, stemming, hole diameter), it gets pushed back to the nearest feasible bound. That way, physically impossible configurations don't slip into the search. Second, any violation of the flyrock safety rule is handled through the penalty term in the objective function—its value increases whenever the predicted flyrock distance crosses the 300 m limit. This hybrid setup keeps the optimizer operating inside geotechnically reasonable regions while still giving it enough freedom to explore the design space.

Consistency between Surrogate Inputs and Inverse-Design Decision Variables

The ANFIS surrogate was trained on six inputs—d, ST/B, C, PF, BI and WI. Meanwhile, the SSO inverse-design stage searched over a wider set

of engineering variables (B, S, ST, C, PF, H, D, Hr). To keep the surrogate and the inverse-design step speaking the same “input language,” each SSO-generated candidate was mapped deterministically onto the six-dimensional surrogate-input vector. Concretely: (i) ST/B was computed straight from the SSO-generated stemming and burden; (ii) C was pulled directly from the SSO design vector; (iii) PF was shared between both spaces without modification; (iv) BI and WI stayed fixed as bench-specific constants during optimization. This physically grounded mapping made sure every candidate fed into the surrogate stayed inside its valid input domain—basically avoiding any out-of-distribution evaluations.

Surrogate Modeling Assumptions for the Inverse Optimization Phase

The inverse design process relies completely on the SSpiderO-ANFIS surrogate to evaluate each candidate blasting configuration. To keep this surrogate-based search on solid ground, the SSO optimizer was kept inside the empirical bounds of the historical blasting dataset. That way, the search stayed in the surrogate's interpolation region instead of wandering off into extrapolated areas where things got unreliable. This constraint cut down surrogate-induced uncertainty and made sure SSO only explored parts of the design space where the model behaved in a stable, predictable way. The narrow and symmetric residual distributions obtained for SSpiderO-ANFIS further support its reliability within these ranges, collectively justifying its use as the evaluator in the inverse optimization stage.

Model Evaluation Criteria

The performance of the proposed metaheuristic-ANFIS models was evaluated using statistical indicators that jointly measure accuracy, reliability and generalization. Four widely used metrics were employed: coefficient of determination (R^2), root mean square error (RMSE), mean absolute error (MAE) and mean absolute percentage error (MAPE). These metrics give different views of the prediction quality from overall explanatory power to absolute and relative error.

Table 5. Performance comparison (R^2 , RMSE, MAE, MAPE for training/testing)

Model name	Training				Testing			
	R^2	RMSE	MAE	MAPE	R^2	RMSE	MAE	MAPE
SSpiderO-ANFIS	0.762	29.330	22.991	0.320	0.818	24.150	20.209	0.271
BSA-ANFIS	0.773	28.636	22.208	0.286	0.799	25.380	18.704	0.205
DO-ANFIS	0.721	31.753	24.236	0.367	0.772	27.032	21.699	0.322
EHO-ANFIS	0.620	37.021	26.169	0.315	0.756	27.990	21.924	0.242
FA-ANFIS	0.656	35.228	26.597	0.408	0.661	32.968	24.862	0.357

R^2 : measures the proportion of the variance in the observed data that is explained by the model. A value closer to 1 is better.

$$R^2 = 1 - \frac{\sum_{i=1}^N (y_i - \hat{y}_i)^2}{\sum_{i=1}^N (y_i - \bar{y})^2} \quad (4)$$

where y_i is the observed value, $\hat{y}_i$ is the predicted value, $\bar{y}$ is the mean of observed values, and N is the number of samples.

RMSE: represents the square root of the average squared prediction error. RMSE penalizes large deviations more heavily, making it sensitive to outliers.

$$\text{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2} \quad (5)$$

MAE: indicates the average magnitude of prediction errors without considering their direction. Compared to RMSE, MAE is less sensitive to extreme errors.

$$\text{MAE} = \frac{1}{N} \sum_{i=1}^N |y_i - \hat{y}_i| \quad (6)$$

MAPE: provides a scale-independent measure of accuracy by expressing errors as percentages of actual values.

$$\text{MAPE} = \frac{100}{N} \sum_{i=1}^N \left| \frac{y_i - \hat{y}_i}{y_i} \right| \quad (7)$$

Together these metrics allow to evaluate the proposed models with R^2 (which captures the explanatory power), RMSE (which captures the large errors), MAE (which captures the average absolute deviations) and MAPE (which captures the percentage-based comparisons). These metrics were used across training, testing and cross-validation to ensure the reliability of the performance and generalization.

RESULTS AND DISCUSSION

Performance of Different Metaheuristic-ANFIS Models

Because all the metaheuristic algorithms in this study have their own built-in randomness, each one was run 20 independent times under the same parameter settings. This multi-run setup follows the usual benchmarking practice for population-based optimizers and helps reduce any bias that might creep in just from luck in a single run. For comparing models, the best run—judged by the lowest RMSE on the training set during optimization—was taken as the representative configuration for each metaheuristic. Even though the results tabled only show the best run, an eye was also kept on the mean and standard deviation across all 20 runs to make sure each algorithm behaved in a reasonably stable, robust way. This setup kept the comparison fair and replicable across all the candidate optimizers. The performance of the five hybrid metaheuristic-ANFIS models is summarized in Table 5, and their convergence behavior during training is shown in Figure 8.

In the training stage (Table 5), the SSpiderO-ANFIS and BSA-ANFIS models basically came out as the stronger ones, with higher R^2 (0.762 and 0.773) and lower errors than the rest. Their RMSEs stayed under 30 m (29.33 and 28.64), and their MAEs hovered around 22, which more or less show that they fit the training data reasonably well. In contrast, EHO-ANFIS and FA-ANFIS did not do as well— R^2 dropped to 0.620 and 0.656, and RMSEs jumped to 37.02 and 35.23. This kind of spread suggests that these algorithms had trouble keeping a good balance between searching widely and zooming in at the right time, so they tended to settle too early or just didn't land on good parameter sets.

In the testing phase (Table 5), the generalization results made it clear that SSpiderO-ANFIS had

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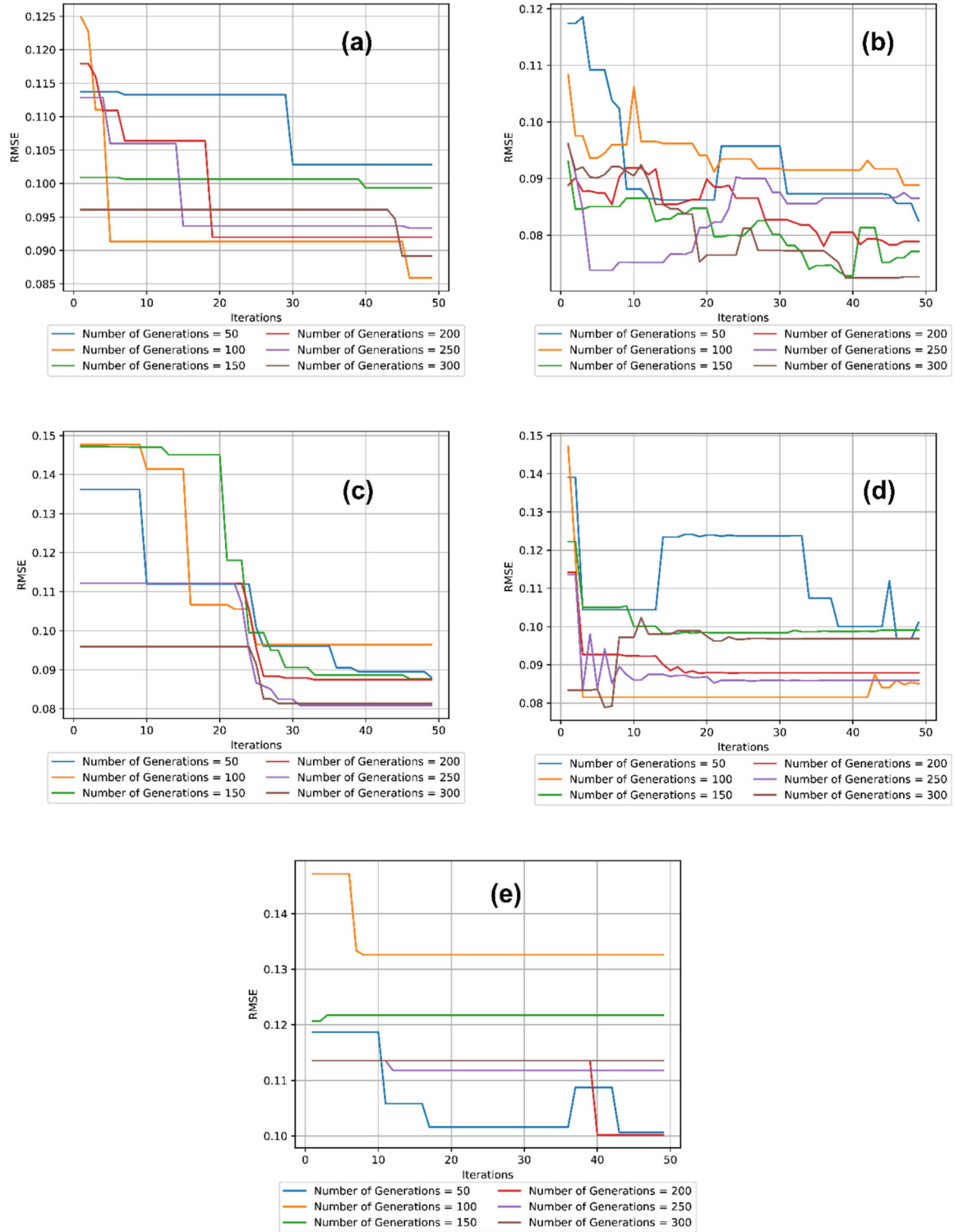


Figure 8. Convergence curves of 5 metaheuristics optimizing ANFIS: (a) SSpiderO-ANFIS; (b) BSA-ANFIS; (c) DO-ANFIS; (d) EHO-ANFIS, (e) FA-ANFIS.

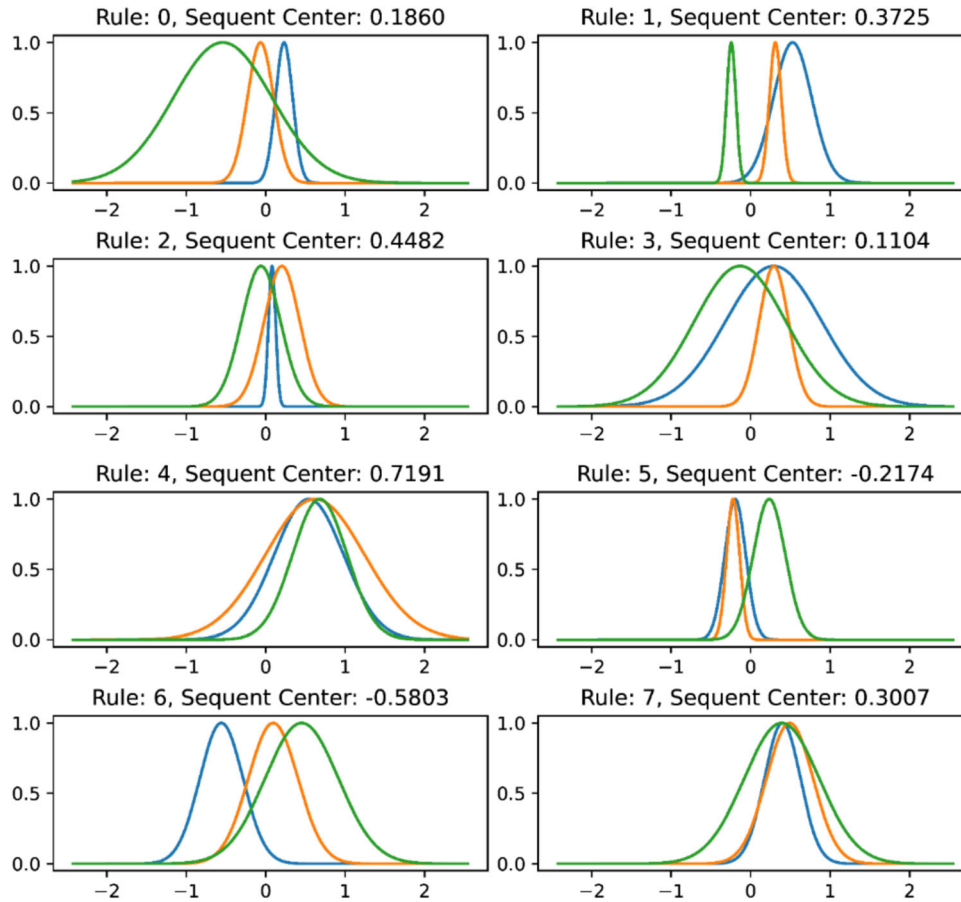


Figure 9. Optimized membership functions of SSpiderO-ANFIS model.

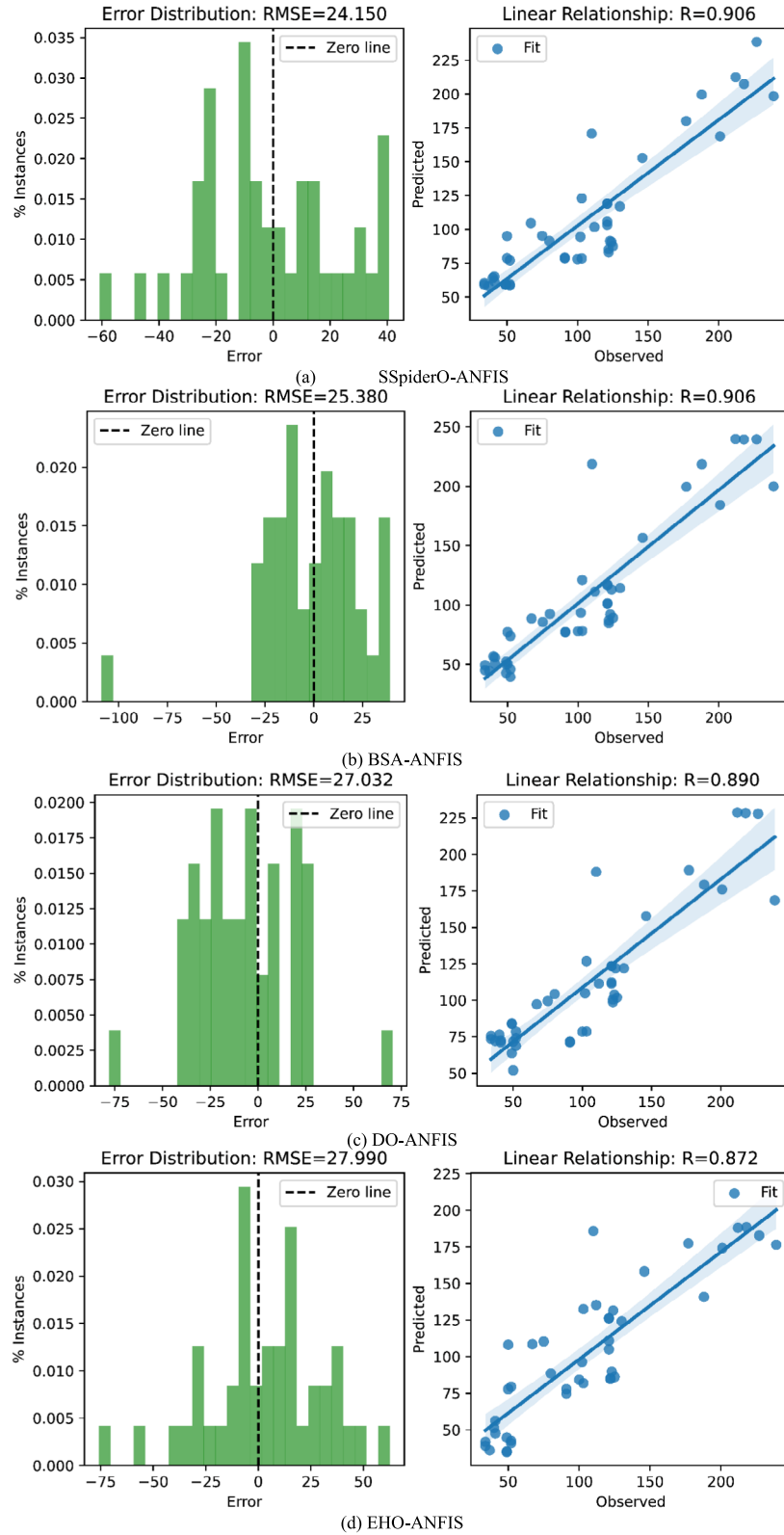
the lead ($R^2 = 0.818$, RMSE = 24.15, MAE = 20.21, MAPE = 0.271). It outperformed the other models by a noticeable margin. BSA-ANFIS still put up a decent result ($R^2 = 0.799$, RMSE = 25.38, MAE = 18.70), and its MAPE (0.205). DO-ANFIS and EHO-ANFIS showed moderate accuracy, with R^2 of 0.756–0.772 and RMSEs above 27. The FA-ANFIS model performed the worst ($R^2 = 0.661$, RMSE = 32.97, MAPE = 0.357), implying that it struggled with the nonlinear nature of the flyrock problem.

Even though the MAPEs of these hybrid ANFIS-metaheuristic models (0.27–0.40) might look a bit high when comparing them to regular regression tasks, in flyrock prediction this is actually quite normal. Flyrock behavior varies a lot because geology changes, block sizes shift, stemming is not always consistent, and even weather plays a role. These things bring uncertainty that no deterministic model can really clean up. Field studies even report

deviations of 50–100% between blasts that look similar on paper. Thus, percent-based errors tend to get blown up when the target variable spans a very wide range. Because of that, practical engineering guidelines usually lean more on absolute performance (e.g., RMSE < 15–20 m) rather than percent errors. Viewed through that lens, the RMSEs here were strong, and the MAPEs were basically in the range expected in real blasting.

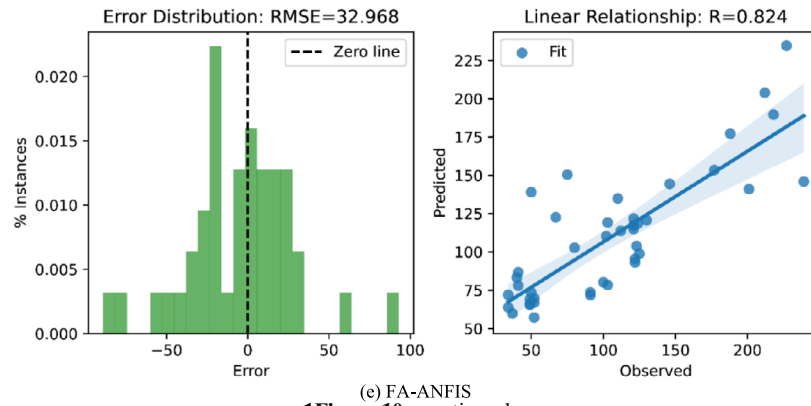
The convergence curves in Figure 8 also give a bit of insight into how the algorithms actually behaved. SSpiderO and BSA both dropped their error quickly in the early iterations and settled at lower RMSEs, suggesting that they searched efficiently and exploited well. EHO and FA moved slow and got stuck in higher-error regions, hinting that their exploration just was not enough. DO did somewhat better but still did not reach the lower region that SSpiderO managed.

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◀ **Figure 10.** Observed flyrock vs. flyrock predicted by hybrid models.

All told, the results point clearly to SSpiderO-ANFIS being the best-performing hybrid model here, with solid generalization and stable conver-



(e) FA-ANFIS
◀ **Figure 10.** continued.

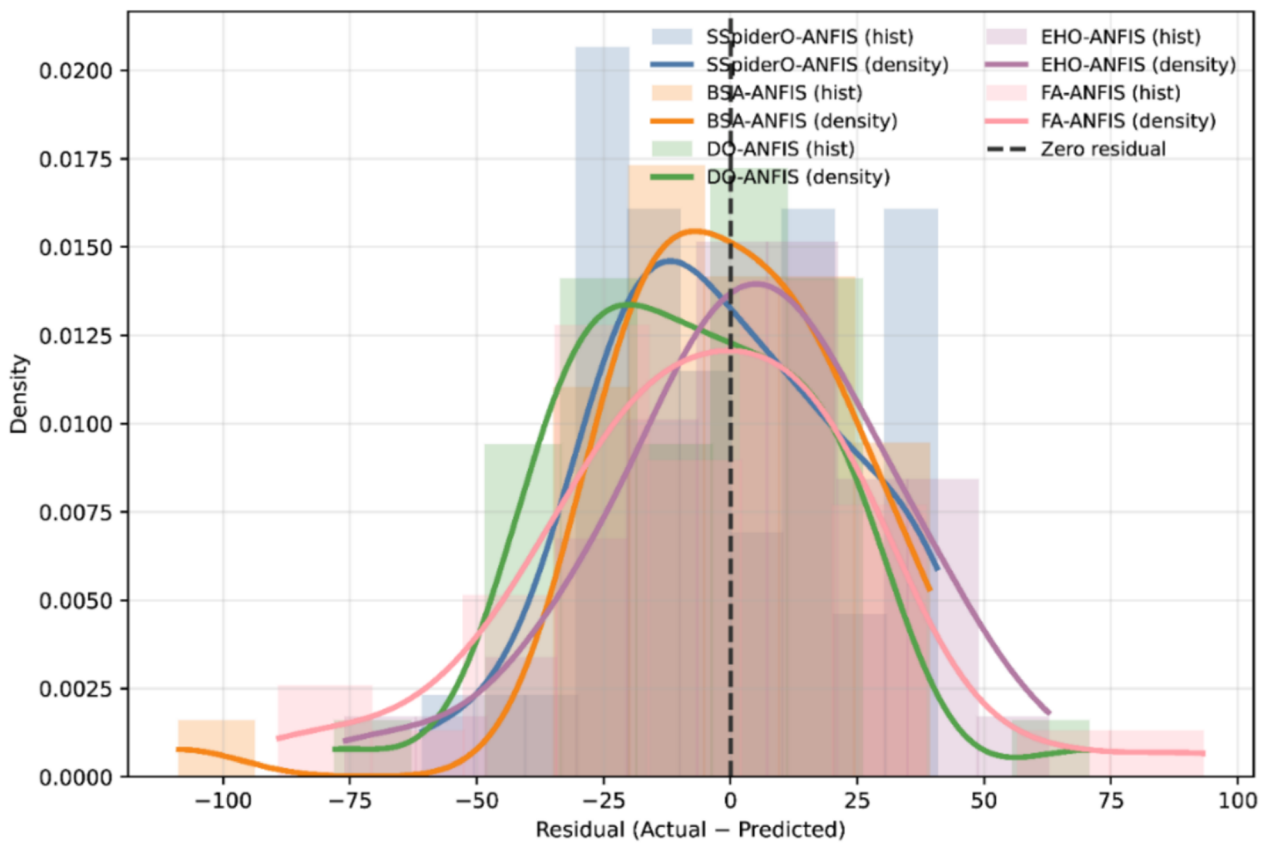


Figure 11. Residual error distributions of five models (overlay).

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gence. While BSA-ANFIS provided competitive outcomes, the superior balance between exploration and exploitation in SSpiderO allowed it to achieve the highest testing R^2 and lowest RMSE, justifying its selection as the surrogate predictor in the subsequent inverse optimization phase. Figure 9 shows the optimized membership functions of the SSpiderO-ANFIS model in predicting flyrock distance in this study.

Selection of best model

The reliability of each hybrid model was further examined by analyzing scatter plots of predicted vs. observed flyrock distances (Fig. 10) and the distribution of residual errors (Fig. 11). As shown in Figure 10, the SSpiderO-ANFIS model gave predictions that sit close to the 1:1 line, with only small scatter and not much noticeable bias across the whole flyrock range. The BSA-ANFIS model also lined up reasonably well, the spread getting a bit wider at the higher flyrock values. DO-ANFIS and EHO-ANFIS showed moderate amounts of scatter—especially for longer-distance flyrock—which hints at some underestimation in those cases. The FA-ANFIS model drifted the most, with predictions pulling away from the observed values quite a lot, basically confirming the weaker performance already seen above in section [Performance of Different Metaheuristic-ANFIS Models](#).

The residual distributions in Figure 11 give a bit more confirmation about how the models behaved. The SSpiderO-ANFIS residuals sit tightly around zero with an even spread on both sides, which suggests low bias and not much variance. BSA-ANFIS residuals are also fairly tight, though there is a slight skew. DO-ANFIS and EHO-ANFIS show wider spreads, meaning their predictions jump around more and aren't as stable. FA-ANFIS, again, shows the broadest and most uneven residual pattern, which lines up with its weak generalization.

From a theoretical angle, the stronger performance of SSpiderO is not really surprising. In SSpiderO, solutions “talk” to each other through vibration-like signals on a shared web. This keeps the population diverse but still lets the search focus more around better candidates. That balance helps a lot when navigating the messy, multimodal error surface that comes with tuning ANFIS parameters. The adaptive attraction–repulsion behavior in SSpiderO also lets it start off exploring widely and

then slowly narrow down into exploitation without locking in too early. Compared to algorithms that move in more rigid patterns—like EHO or FA—SSpiderO's dynamics make it easier to escape local minima when adjusting both the fuzzy premise and consequent parameters. These traits more or less explain why SSpiderO came out on top among the five metaheuristics and why it fits nicely for training the surrogate model used in the inverse blasting optimization stage.

Looking at both the scatter alignment and the residual distributions, SSpiderO-ANFIS stands out as the most reliable and accurate model for flyrock prediction. Its high R^2 , low errors, stable convergence (as shown earlier), and clean residual profile all support using it as the surrogate loss function in the inverse blasting optimization phase.

Sensitivity Analysis

To get a better sense of how robust the framework is, and how interpretable the predictions actually are, a sensitivity analysis was carried out. Each input variable (d , ST/B, C, PF, BI, WI) was nudged around its median value by $\pm 10\%$ and $\pm 20\%$, and the resulting shifts in predicted flyrock distance were recorded. The changes are shown in Figure 12.

The tornado chart shows some clear differences in how each input variable affects the output: (1) d and WI came out the most sensitive. A 20% change in either one led to roughly a 15% shift in flyrock distance, which makes sense because both strongly influence how much energy actually gets into the rock and how the fragmentation behaves. (2) BI was also fairly sensitive, giving deviations up to about 8%. BI captures rock mass quality and fracturability, so its influence isn't too surprising. (3) PF showed moderate sensitivity (around 3–4% at a 20% change), as it basically scales explosive energy relative to the volume of rock. (4) ST/B and C had the smallest effect, with flyrock shifting less than $\sim 2\%$ even under the $\pm 20\%$ perturbation.

Overall, the analysis suggests that geometric design parameters (like d) and geological indicators (WI, BI) were the main drivers of flyrock in this dataset, while the more conventional blasting parameters (PF, ST/B) played a more moderate role. This reinforces the idea that geological indices should not be treated as optional add-ons when

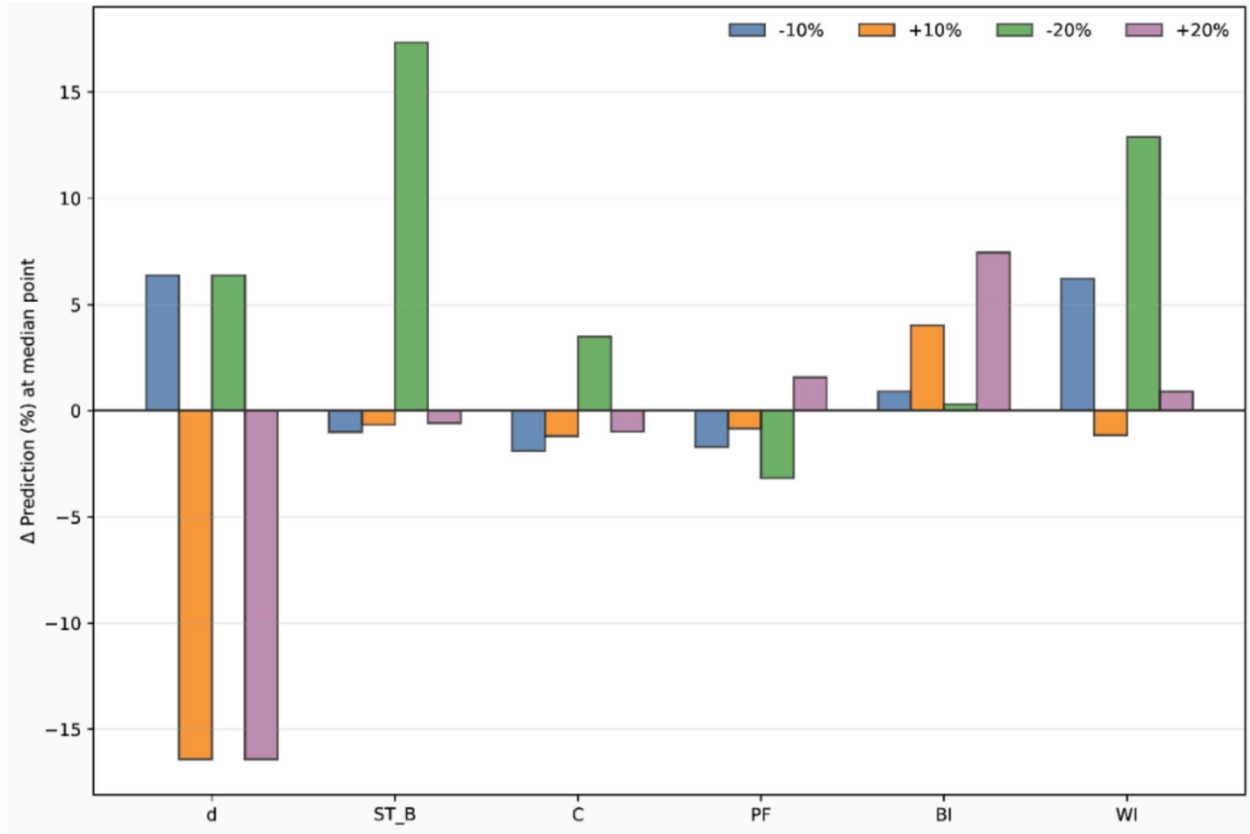


Figure 12. Sensitivity analysis with Tornado chart using one-at-a-time perturbations.

building AI-based flyrock prediction models; they matter quite a lot.

The narrow spreads in the tornado chart (Fig. 12) also show that the SSpiderO-ANFIS model reacted in a consistent way to input changes. That consistency gives a bit more confidence in its robustness and suggests that it is ready for practical use in safe blast design optimization.

Inverse Optimization Using SSO

The second phase of this study used the SSO algorithm for the inverse blasting design. In this setup, the SSpiderO-ANFIS model—basically the best performer earlier—was placed in as the surrogate fitness function. With that in place, SSO just moved through feasible blasting settings, trying to pull flyrock down while still keeping the safety limits in place. The whole process is a bit iterative, a bit mechanical, nothing too exotic.

Figure 13 shows how SSO settled over the iterations. At the start, the fitness dropped fast—almost too fast—then the curve slowed and flattened as the search edges toward whatever counts as the optimum here. This pattern suggests that SSO managed a workable mix: wide roaming early on, then tightening the search later, without locking up prematurely. It did not drift forever either; the motion sort of tapered off in a natural way.

To make better sense of the optimization results, Figure 14 sketches how the input–output mapping behaved. It shows the nonlinear way blasting parameters push the predicted flyrock distance around. In particular, ST vs. S followed a kind of monotonic increasing trend that helped bring flyrock down, while PF tended to drop as the model adjusted things toward the safety target. These nonlinear patterns basically underline why inverse modeling is handy here—it captures design–response interactions that empirical rules just cannot represent well.

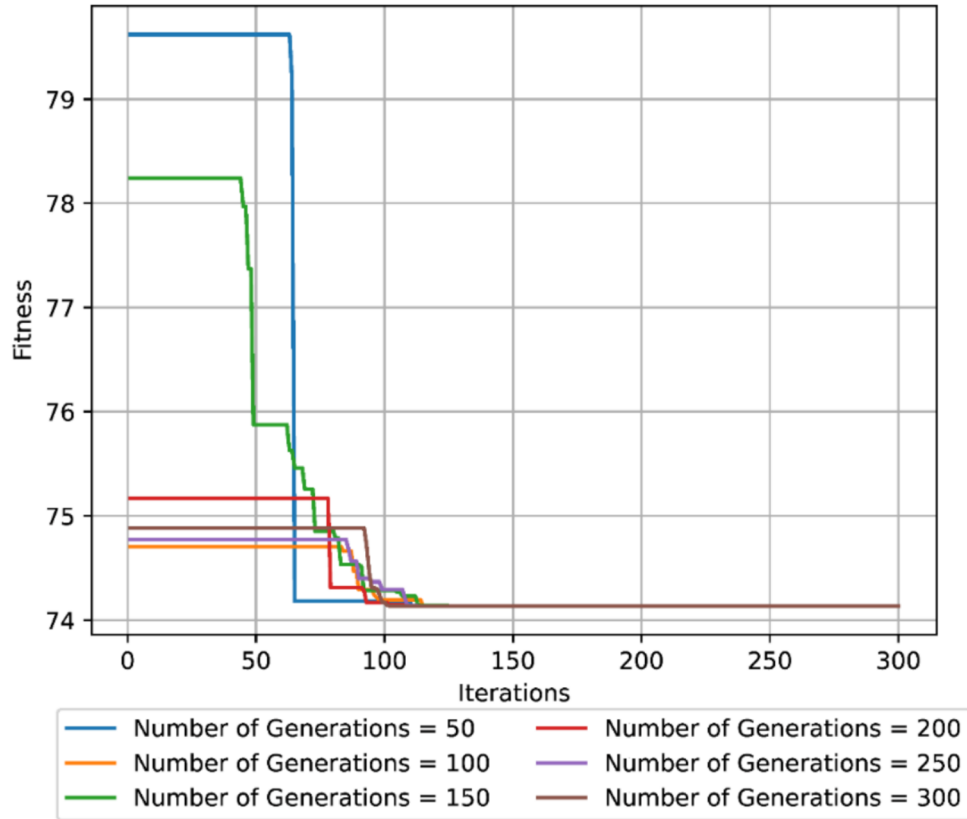


Figure 13. Convergence profile of SSO during inverse blasting optimization.

The final optimized set of blasting parameters from the SSO is given in Table 6. Compared with the baseline, the optimal design included (i) a small bump in B from 3.5 to 4.2 m, (ii) a moderate increase in S from 4.0 to 4.5 m, (iii) a noticeable rise in ST from 2.8 to 3.3 m, and (iv) a reduced PF from 0.65 to 0.48 kg/m³. The other parameters— C , d , BI , and WI —stayed stable within reasonable ranges.

Overall, the inverse optimization results show that even modest tweaks to geometric design (B , S , ST), combined with a lower PF , are enough to keep flyrock under the 300 m safety threshold. This gives engineers some practical room to set up blasting operations in a way that meets safety needs while still keeping energy use in check for surface mining conditions.

Comparative Discussion with Literature

To give the proposed hybrid framework some context, it helps to line it up against what other re-

searchers have done before. Empirical models—like the well-known USBM equation—are still used a lot because they are simple and quick to apply. But, the trade-off is that they kind of flatten the complicated interactions between blasting parameters and geological conditions, which usually leads to modest predictive accuracy. When ML techniques came in—like regression trees, SVM, or multilayer perceptrons (MLP)—they pushed the performance further by capturing the nonlinear bits that empirical formulas just miss. Nevertheless, many ML studies in blasting applications are limited by their reliance on single-algorithm frameworks, which are prone to local minima and generalization issues.

Metaheuristic-ML hybrids have emerged as a more recent trend, with optimizers such as genetic algorithm (GA), particle swarm optimization (PSO), and ant colony optimization (ACO) used to fine-tune model parameters (Koopialipoor et al., 2019; Patil et al., 2020; Jithendra & Basha 2023). Representative examples include ANFIS-GOA (Fattahi & Hasanipanah 2022), MSHHO-SVR (Li et al.,

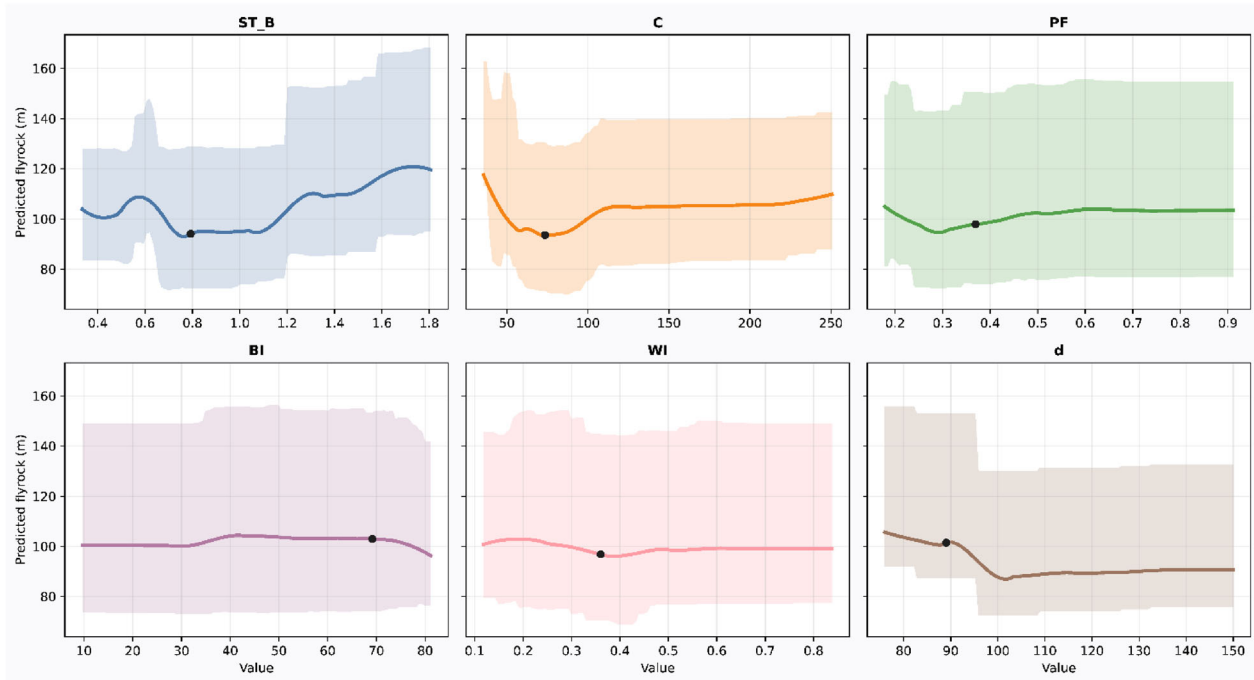


Figure 14. Example of input–output mapping curve illustrating nonlinear relationships between blasting parameters and flyrock outcomes.

Table 6. Optimized blasting parameter configurations obtained using SSO to achieve safe flyrock distances (<300 m)

Parameter	Unit	Baseline (mean)	Optimized range (from SSO 2search)	Optimal value (SSO result)	Change trend
Burden (B)	m	3.5	3.0–4.5	4.2	↑ Slight increase
Spacing (S)	m	4.0	3.5–5.0	4.5	↑ Moderate increase
Stemming length (ST)	m	2.8	2.5–3.5	3.3	↑ Increase
Charge per hole (C)	kg	120	100–140	118	≈ Stable (slight decrease)
Powder factor (PF)	kg/m ³	0.65	0.35–0.65	0.48	↓ Decrease
Hole diameter (d)	mm	150	150–170	150	≈ Stable
Blastability Index (BI)	–	7.2	7.0–7.5	7.3	≈ Stable
Weathering Index (WI)	–	0.42	0.40–0.45	0.43	≈ Stable

2023), and boosted deep-kernel models, which have reported substantial gains in forward predictive accuracy for flyrock. However, these approaches remain essentially forecast-oriented and do not provide prescriptive guidance on how to adjust blasting parameters in order to satisfy safety constraints. Very few studies have addressed the more challenging inverse optimization problem, i.e., determining safe and feasible blasting configurations that constrain flyrock within prescribed limits. In contrast, the present study not only integrates mul-

tiple metaheuristic optimizers (SSpiderO, BSA, DO, EHO, FA) to enhance ANFIS predictive performance, but also introduces a second-phase inverse optimization using SSO. This two-stage framework bridges the gap between predictive modeling and practical design application. As summarized in Table 7, the proposed SSpiderO-ANFIS + SSO model clearly outperformed traditional empirical and ML models in terms of accuracy, robustness, and practical applicability to safe blast design.

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Table 7. Comparison with previous models (empirical, ML, metaheuristic)

Category	Typical methods/examples	Strengths	Limitations	Position of present study
Empirical models	USBM, Langefors–Kihlström	Simple, easy to apply	Oversimplified, poor accuracy	Outperformed by AI-based models
Statistical models	Regression, multivariate analysis	Capture linear trends	Limited for nonlinear blasting data	Surpassed by hybrid approach
ML models	ANN, SVM, MLP	Handle nonlinearities	Local minima, moderate generalization	Improved via metaheuristic training
Hybrid meta-heuristic-ML	GA-ANN, PSO-ANFIS, ACO-SVM	Higher accuracy, robust training	Focus only on forward prediction	Present study extends to inverse design
Present study	Multi-metaheuristic ANFIS + SSO (2-phase)	Best prediction + actionable optimization	Novelty: integrates inverse optimization	New contribution

Relation to Probabilistic and Risk-Based Blast Design Frameworks

Although the inverse design stage in this study is formulated deterministically using a fixed regulatory threshold of 300 m, it is useful to contextualize this approach in relation to emerging probabilistic frameworks for blast-induced hazard assessment. Recent studies have proposed reliability-based or exceedance-probability formulations in which the objective is not only to meet a deterministic limit but also to ensure that the likelihood of exceeding that limit remains acceptably low. While implementing a full probabilistic model is beyond the present scope, the 2-phase structure developed here is fully compatible with such extensions: the SSpiDerO-ANFIS surrogate can be used to estimate uncertainty-aware response surfaces, and the SSO search procedure can be adapted to incorporate risk measures (e.g., chance constraints or safety factors). The deterministic design presented here thus serves as a computationally efficient baseline that aligns with current regulatory practice while offering a clear pathway toward future risk-informed blasting strategies.

Practical Implications

The outcomes of this study extend beyond theoretical contributions and offer direct value to engineering practice in surface mine blast design. By integrating the proposed 2-phase framework (SSpiDerO-ANFIS prediction + SSO inverse optimization) into the blasting workflow, engineers can achieve safer and more efficient designs.

In practice, engineers usually fall back on empirical rules or some round-after-round tweaking to set up burden, spacing, stemming, and the powder factor. This way works, but it's slow and inconsistent, especially when the rock mass is all over the place. The framework proposed here acts like a data-driven decision-support system: (1) Prediction phase—Engineers just plug the site-specific blast design variables and rock properties into the trained SSpiDerO-ANFIS model, and it gives a fairly accurate estimate of the flyrock distance. (2) Inverse optimization phase—If that predicted flyrock goes beyond the safety limit, the SSO algorithm automatically adjusts the controllable design variables (like stemming, burden, spacing) and spits out an optimized plan that stays within regulations. (3) Implementation phase—The optimized design can then be fed straight into the blast design software and field operations, which cuts down a lot of the usual trial-and-error.

The practical benefits are clear: (1) Better safety: By keeping predicted flyrock under a set threshold (say, 300 m), the framework basically gives a quantitative safety check and reduces risk for workers, machines, and nearby structures. (2) Less trial-and-error: Traditional blasting often means many field trials just to fine-tune things. The proposed model takes out most of that uncertainty by offering recommendations that are already validated. (3) Cost efficiency: With more efficient parameter sets, explosive waste drops, secondary breakage is reduced, and the chance of delays caused by safety issues goes down. Overall blasting becomes smoother and cheaper per cubic meter of rock. (4) Support under variable conditions: Because the model captures the messy nonlinear interactions between parameters, it still gives stable guidance

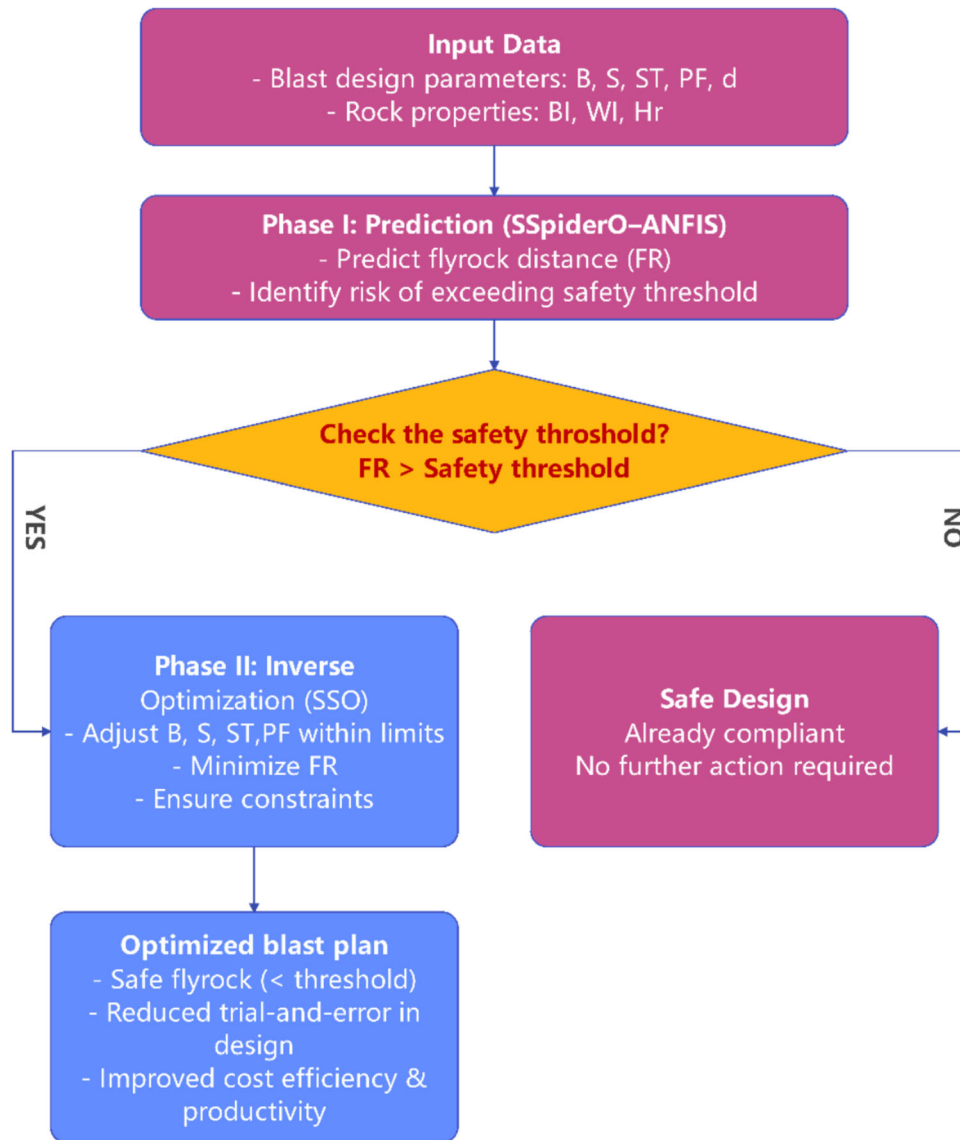


Figure 15. Practical application scheme of the 2-phase framework (SSpiderO-ANFIS + SSO) integrated into blast planning.

even when geological conditions shift and empirical rules stop making sense.

Figure 15 sketches how the 2-phase framework (SSpiderO-ANFIS + SSO) fits into real blast planning.

CONCLUSION

This paper proposes a novel 2-phase hybrid framework for predicting and controlling blast-in-

duced flyrock in surface mining operations. The key findings and contributions can be summarized as follows:

1. Hybrid metaheuristic-ANFIS modeling. Five state-of-the-art metaheuristic algorithms (SSpiderO, BSA, DO, EHO, FA) were employed to optimize ANFIS parameters for flyrock prediction. Among them, the SSpiderO-ANFIS model demonstrated superior performance with the

Hybrid Metaheuristic-ANFIS Framework for Predicting

- highest accuracy and stability across evaluation metrics.
2. Robust prediction and validation. Through systematic evaluation and sensitivity analysis, the proposed model successfully captured nonlinear and complex interactions between blast design variables and rock mass properties. The framework provided reliable predictive capability, supporting its applicability in variable mining environments.
 3. Inverse optimization. Building on the best-performing SSpiderO-ANFIS model, the second phase integrated SSO for inverse design. This enabled the determination of safe blasting configurations that restrict flyrock within prescribed thresholds, thereby directly bridging predictive modeling with practical blast design.
 4. Practical implications. The 2-phase system reduces reliance on empirical rules and trial-and-error approaches, offering a decision-support tool for engineers to achieve safer, more cost-efficient, and regulation-compliant blast designs.

Despite these advances, certain limitations should be acknowledged. The dataset used was relatively limited in size and scope, which may constrain the generalizability of the results to other mines with significantly different geological or operational conditions. Moreover, the study primarily focused on single-objective optimization (minimizing flyrock), while ignoring other blast outcomes such as ground vibration, air overpressure, or fragmentation.

To address these limitations, future research should explore: (a) multi-objective optimization frameworks that simultaneously balance safety, fragmentation efficiency, and environmental impacts; (b) larger and more diverse datasets across different mining sites to enhance generalization; and (c) advanced learning paradigms such as transfer learning or domain adaptation to extend model applicability across heterogeneous geological and operational conditions.

In addition, the 2-phase predictive–prescriptive framework developed in this study opens several avenues for further development. First, the inverse design stage could be extended to a true multi-objective formulation in which flyrock mitigation is jointly optimized with fragmentation quality, blast-induced ground vibration, or explosive consumption. Second, incorporating uncertainty in input vari-

ables—such as variability in BI/WI, the stability of the stemming column, or drilling deviations—would allow the construction of probabilistic or reliability-based optimization models capable of quantifying the likelihood of exceeding safety thresholds.

Finally, while the present study employed a deterministic mapping to reconcile the eight-dimensional design space with the six-dimensional surrogate-input space, future work may consider hierarchical or physics-informed mappings that better capture coupled effects between geometric, explosive, and geomechanical parameters.

Overall, the proposed hybrid SSpiderO-ANFIS + SSO workflow represents a significant advancement in both forward prediction and inverse optimization for blast design, providing a strong foundation for safer, more efficient, and more intelligent mining operations.

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DECLARATIONS

Conflict of Interest The authors declare that they have no known conflict of financial interest or personal relationships that could have appeared to influence the work reported in this paper.

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