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ORIGINAL ARTICLE

A new hybrid ANFIS–PSO model for prediction of peak particle velocity due to bench blasting

Ebrahim Ghasemi[1] · **Hamid Kalhori**[1] · **Raheb Bagherpour**[1]

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Abstract In this paper, a novel hybrid approach is proposed for predicting peak particle velocity (PPV) due to bench blasting in open pit mines. The proposed approach is based on the combination of adaptive neuro-fuzzy inference system (ANFIS) and particle swarm optimization (PSO). In this approach, the PSO is used to improve the performance of ANFIS. Furthermore, a model is developed based on support vector regression (SVR) approach. The models are trained and tested based on actual data compiled from 120 blast rounds in Sarcheshmeh copper mine. To determine the accuracy and efficiency of ANFIS–PSO and SVR models, a statistical model (USBM equation) is applied. According to the obtained results, both techniques can be used to predict the PPV, but the comparison of models shows that the ANFIS–PSO model provides better results. Root mean square error (RMSE), variance account for (VAF), and coefficient of determination (R^2) indices were obtained as 1.83, 93.37 and 0.957 for ANFIS–PSO model, respectively.

Keywords Bench blasting · PPV · ANFIS · PSO · SVR

1 Introduction

Although blasting is one of the important basic operations for production cycle in mines, this operation has always been accompanied by some undesirable effects. Ground vibration is one of these destructive effects, which has been the main concern of environmentalists. In fact, ground vibration is acoustic waves that propagate through the ground [1–3]. When an explosive charge detonates in the blasthole, intense dynamic stresses are set up around it due to sudden acceleration of the rock mass by detonating gas pressure on blasthole wall. The strain waves transmitted to the surrounding rock set up a wave motion in the ground [4, 5]. The strain energy carried out by these strain waves fragments the rock mass due to different breakage mechanisms such as crushing, radial cracking, and reflection breakage in the presence of a free face. The crushed zone and radial fracture zone encompass a volume of permanently deformed rock. When the stress wave intensity diminishes to the level where no permanent deformation occurs in the rock mass (i.e., beyond the fragmentation zone), strain waves propagate through the medium as the elastic waves, oscillating the particles through which they travel. These waves in the elastic zone are known as ground vibration, which closely conform to the visco-elastic behavior. The wave motion spreads concentrically from the blast site in all directions and gets attenuated due to spreading of fixed energy over a greater mass of material and away from its origin [6]. Even though, the ground vibration attenuates exponentially with distance but due to large quantity of explosive, it can still be high enough to threaten the safety and stability of surrounding structures because of dynamic stresses that exceed material strength [7]. This phenomenon can create great socioeconomic problems for the mine management as well as for people residing in the vicinity of the mine. High level of ground vibration has harmful effects on the structural integrity, ground water, and ecology of the nearby area. To minimize these harmful effects, mining and blasting engineers should monitor and assess the ground vibration phenomenon, carefully. Peak particle velocity (PPV) is the most practical indicator

✉ Ebrahim Ghasemi
e_ghasemi@cc.iut.ac.ir; ebrahim62.gh@gmail.com

1 Department of Mining Engineering, Isfahan University of Technology, Isfahan, P.O. Box 8415683111, Iran

Table 1 Most common empirical equations for PPV prediction

Name	Equation	References
USBM	$PPV = K \cdot \left[D/Q^{1/2}\right]^{-B}$	[13]
Langefors–Kihlstrom	$PPV = K \cdot \left[Q^{1/2}/D^{3/4}\right]^{B}$	[14]
General predictor	$PPV = K \cdot D^{-B} \cdot Q^{A}$	[15]
Ambraseys–Hendorn	$PPV = K \cdot \left[D/Q^{1/3}\right]^{-B}$	[16]
Indian standard	$PPV = K \cdot \left[Q/D^{2/3}\right]^{B}$	[17]
Ghosh–Daemen 1	$PPV = K \cdot \left[D/Q^{1/2}\right]^{-B} \cdot e^{-\alpha D}$	[18]
Ghosh–Daemen 2	$PPV = K \cdot \left[D/Q^{1/3}\right]^{-B} \cdot e^{-\alpha D}$	[18]
Gupta et al.	$PPV = K \cdot \left[D/Q^{1/2}\right]^{-B} \cdot e^{-\alpha (D/Q)}$	[19]
CMRI predictor	$PPV = n + K \cdot \left[D/Q^{1/2}\right]^{-1}$	[20]
Rai–Singh	$PPV = K \cdot D^{-B} \cdot Q^{A} \cdot e^{-\alpha D}$	[21]

PPV is peak particle velocity (mm/s), *Q* is maximum charge per delay (kg), *D* is distance between the blasting source and vibration monitoring point (m), and *K*, *A*, *B*, *α*, *n* are site constants

for assessment of this phenomenon. Many researchers have suggested several criteria for evaluation of blast-induced damage based on this indicator [5–12].

During past years, several empirical equations have been presented for PPV prediction (Table 1). The most widely used predictor equation for PPV is square-root scaling proposed by the United States Bureau of Mines (USBM equation). Two main disadvantages of these equations are: (1) the empirical equations are site specific and are not suitable for other sites, and (2) these equations are based on only two parameters, maximum charge per delay and distance from blast location, and do not include other effective parameters [22].

Recently, new approaches have attracted the attention of researchers for prediction of PPV, which are based on soft computing techniques. The studies indicate that the efficiency and accuracy of these approaches is more than empirical methods by a wide margin. Thus, nowadays these approaches are applied extensively for PPV prediction. For example, artificial neural network (ANN) [4, 23–40], fuzzy logic (FL) [22, 28, 41], adaptive neuro-fuzzy inference system (ANFIS) [42–47], support vector regression (SVR) [48–54], genetic algorithm (GA) [55], hybrid artificial neural network and imperialist competitive algorithm (ANN-ICA) [56], and hybrid artificial neural network and particle swarm optimization (ANN-PSO) [57, 58] have been applied for this purpose successfully.

The study presented herein aims to predict the PPV based on two soft computing techniques; hybrid adaptive neuro-fuzzy inference system and particle swarm optimization (ANFIS–PSO) and support vector regression (SVR). For this purpose, a database compiled from Sarcheshmeh copper mine was used and the models were developed based on major blasting parameters.

In spite of being applied in various fields widely, the literature surveys show that there is no study about the application of ANFIS–PSO in the field of mining [59–64]. Hence, an effort has been made in this paper to make use of ANFIS–PSO for PPV prediction. As mentioned before, recently some models have been developed for PPV prediction due to bench blasting based on SVR approach [48–54]. In most of these models, the PPV value is estimated considering only two parameters, i.e., charge weight per delay and distance from blast location, whereas this study not only considers these two parameters but also other effective parameters on ground vibration, such as burden, spacing, stemming and number of blastholes per delay.

To assess the performances of ANFIS–PSO and SVR models, the prediction capacity of these models is compared with USBM empirical equation developed based on Sarcheshmeh copper mine database.

This paper is organized as follows: the mine description and the structure of database are explained in Sect. 2. In Sects. 3, 4, and 5, ANFIS–PSO, SVR and USBM models are constructed for PPV prediction in Sarcheshmeh copper mine, respectively. The performances of proposed models are examined and compared with each other in Sect. 6 and finally, the paper is concluded in Sect. 7.

2 Description of database

As mentioned before, a database compiled from Sarcheshmeh copper mine is used in this study. Sarcheshmeh copper mine is the biggest open pit porphyry copper mine in Iran which is located 160 km southwest of Kerman [22, 29]. In this mine, blasting operation is performed for rock excavation. ANFO is used as the main explosive material and dynamite cartridges are used as primer with bottom hole positioning. The blasting system is non-electric and detonating cord is applied for initiation. Blastholes are drilled vertically in a staggered pattern and drilling cuttings are used as stemming materials. The diameter and depth of blastholes are 215 mm and 15 m, respectively.

The database is composed of 120 blast events and includes 8 parameters (see Table 2). Burden, spacing, stemming, number of blastholes per delay, maximum charge per delay, distance from blast location to monitoring point, and PPV were recorded in each blast event. Burden, spacing and stemming were measured by a tape meter and number of blastholes per delay by controlling each blasting pattern. The distance from the blasting location to the monitoring point was measured carefully by means of a hand-held GPS (global positioning system) and the amount of maximum charge per delay was recorded for each blast by controlling the blasthole charge. Furthermore, the amount of dynamite used as priming was considered for determining

Table 2 Basic descriptive statistics for Sarcheshmeh copper mine database

Parameters	Unit	Min.	Max.	Mean	Standard deviation
Burden	m	3.00	7.50	7.01	1.13
Spacing	m	4.00	11.00	9.29	1.75
Stemming	m	2.40	6.00	5.51	0.95
No. of holes per delay	–	6.00	32.00	14.08	5.33
Charge per delay	kg	1332.00	9812.00	5595.21	2079.04
Distance from blast location	m	133.00	2845.00	1037.47	591.04
PPV	mm/s	0.49	53.55	9.31	9.00

Table 3 Main parameters of the PSO

Parameters	Value
Number of particles	20
Number of iterations	200
Cognitive acceleration (c_1)	2
Social acceleration (c_2)	2
Initial inertia weight ($\omega_{\min}$)	0.9
Final inertia weight ($\omega_{\max}$)	0.4

the maximum charge per delay. PPV was measured by digital seismograph of PDAS-100 (Portable Data Acquisition System), which measures PPV in three orthogonal directions. The dynamic range of this seismograph is more than 96 dB, with frequency range between 2 and 250 Hz, sampling rate of 300 sample per second, and trigger levels of 0.1–250 mm/s.

It should be mentioned that in all of recorded blasts, diameter of blastholes, depth of blastholes and delay time between blastholes are constant and equal to 152 mm, 15 m and 50 ms, respectively. The range of collected data is summarized in Table 2.

For developing the proposed models, the database was divided into two groups randomly: one group for developing predictive models including 80 % of the cases (i.e., 96 blasts) and the other group including the rest of the cases (i.e., 24 blasts) for testing the models' performances.

3 Development of ANFIS–PSO model

The adaptive neuro-fuzzy inference system (ANFIS) is a learning algorithm which was first introduced by Jang [65]. Furthermore, particle swarm optimization (PSO) is a heuristic global optimization method developed originally by Kennedy and Eberhart [66] based on the research of bird and fish flock movement behavior. Since the details about the algorithm and mathematical of ANFIS and PSO can be found in numerous literatures [65–69], they are not explained in this paper.

In this section, a PPV estimation model is developed using a novel hybrid approach. In this model, the ANFIS framework is optimized by PSO to improve the performance of ANFIS. In fact, ANFIS provides the search space and employs PSO for finding the best solution by tuning

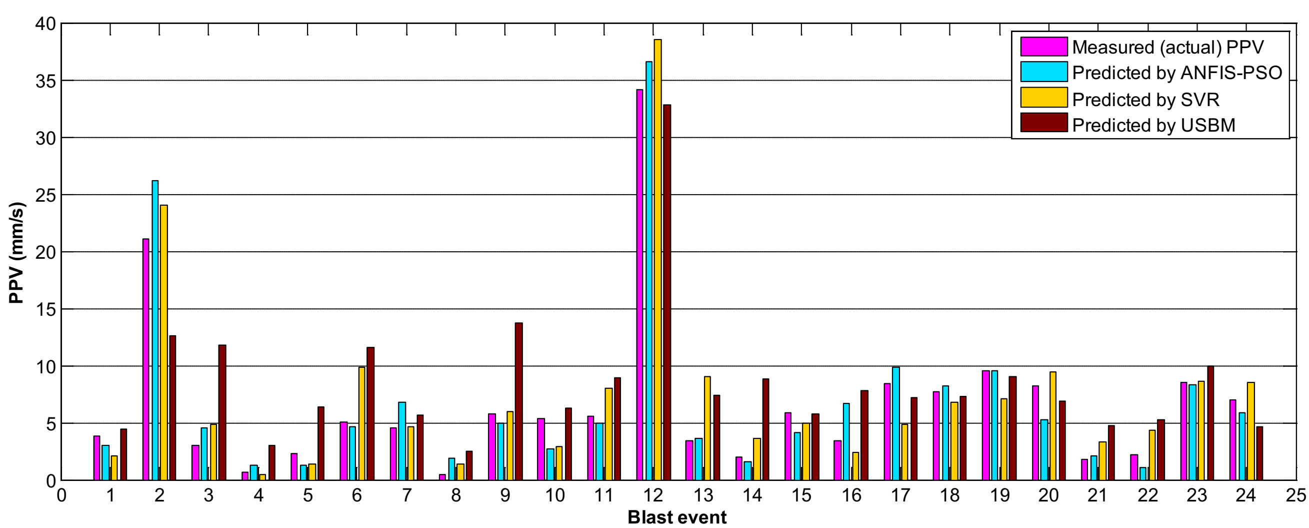

Fig. 1 Comparison of measured and predicted PPV values by different models

Table 4 Measured and predicted PPV values by ANFIS–PSO, SVR and USBM models for testing datasets

Blast no.	Measured PPV (mm/s)	ANFIS–PSO model		SVR model		USBM model	
		Predicted PPV (mm/s)	Error	Predicted PPV (mm/s)	Error	Predicted PPV (mm/s)	Error
1	3.80	3.00	0.8	2.12	1.68	4.44	−0.64
2	21.05	26.22	−5.17	23.99	−2.94	12.64	8.41
3	3.03	4.50	−1.47	4.84	−1.81	11.80	−8.77
4	0.66	1.30	−0.64	0.50	0.16	3.00	−2.34
5	2.27	1.26	1.01	1.34	0.93	6.33	−4.06
6	5.02	4.60	0.42	9.88	−4.86	11.56	−6.54
7	4.50	6.80	−2.3	4.66	−0.16	5.62	−1.12
8	0.49	1.90	−1.41	1.35	−0.86	2.53	−2.04
9	5.74	4.90	0.84	6.01	−0.27	13.74	−8.00
10	5.34	2.70	2.64	2.91	2.43	6.23	−0.89
11	5.57	5.00	0.57	8.06	−2.49	8.88	−3.31
12	34.10	36.56	−2.46	38.48	−4.38	32.79	1.31
13	3.45	3.61	−0.16	9.06	−5.61	7.38	−3.93
14	2.00	1.59	0.41	3.61	−1.61	8.79	−6.79
15	5.91	4.14	1.77	4.97	0.94	5.74	0.17
16	3.44	6.70	−3.26	2.39	1.05	7.82	−4.38
17	8.37	9.83	−1.46	4.81	3.56	7.20	1.17
18	7.75	8.20	−0.45	6.79	0.96	7.29	0.46
19	9.55	9.50	0.05	7.14	2.41	9.07	0.48
20	8.20	5.24	2.96	9.44	−1.24	6.84	1.36
21	1.76	2.10	−0.34	3.29	−1.53	4.78	−3.02
22	2.19	1.03	1.16	4.36	−2.17	5.24	−3.05
23	8.50	8.33	0.17	8.61	−0.11	9.93	−1.43
24	6.98	5.91	1.07	8.54	−1.56	4.64	2.34

Table 5 Performance indices (RMSE and VAF) for various models

Model	RMSE	VAF
ANFIS–PSO	1.83	93.37
SVR	2.40	89.49
USBM	4.11	73.00

the membership functions required to achieve lower error rates. The error between the model output and the actual training data can reach a minimum value through the iteration of the PSO algorithm.

The ANFIS–PSO approach was coded with Matlab software package. ANFIS–PSO approach is developed to estimate PPV based on major blasting parameters; burden, spacing, stemming, number of blastholes per delay, maximum charge per delay, and distance from blast location to monitoring point. The membership functions considered in this study are Gaussian shaped. Furthermore, the main PSO parameters are given in Table 3. These parameters represent number of particles, maximum number of iterations, initial inertia weight, final inertia weight, personal learning coefficient and global learning coefficient. These parameters are determined by trial and error procedure and are the optimum values for this case study.

4 Development of SVR model

Support vector regression (SVR) is a universal learning algorithm proposed by Vapnik et al. [70] and has been regarded as one of the most significant achievements in machine learning in the last decades. SVR has a strong ability to address nonlinear issues and has been successfully used in a wide range of fields [71–75]. More details about the SVR and its mathematics are given in Vanpik [76].

The SVR model, like ANFIS–PSO model, includes six inputs (burden, spacing, stemming, number of blastholes per delay, maximum charge per delay, and distance from blast location to monitoring point) and one output (PPV). LIBSVM toolbox developed by Chang and Lin [77] was used for constructing the SVR model. The LIBSVM, an integrated software tool for SVR, was run in the Matlab environment. Gaussian radial basis function kernel was selected as the

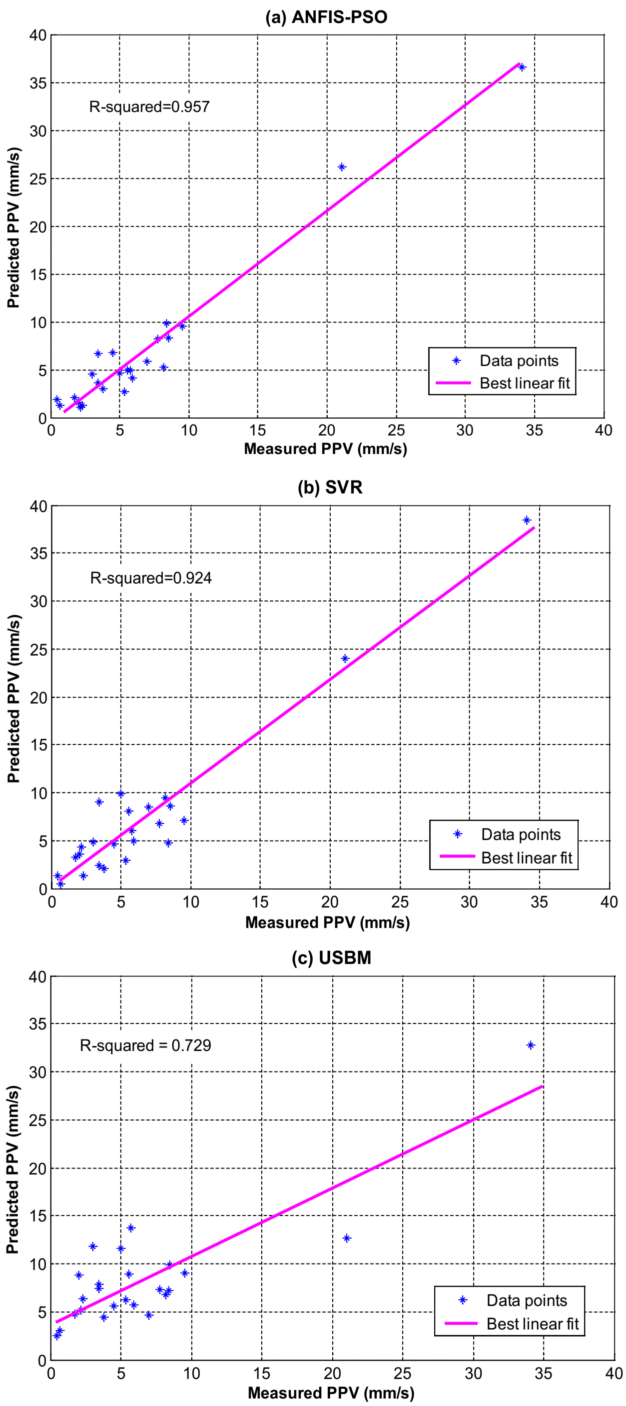

Fig. 2 The relationship between measured and predicted PPV by **a** ANFIS–PSO model, **b** SVR model, and **c** USBM model

kernel function because of its superiority over the other kernel functions. The form of this kernel function is as follows:

$$K\left(x_i, x_j\right) = \exp\left(-\left\|x_i - x_j\right\|^2 / 2g^2\right) \tag{1}$$

where g is the deviation (width) of the RBF kernel.

The main parameters for model development are the penalty factor C, and the radial basis function kernel deviation g. The values of these two parameters greatly affect the training and generalization capability of the SVR. In LIBSVM software, C and g are obtained via a grid searching method coupled with cross validation [77].

5 Development of USBM equation

As mentioned previously, the USBM equation is the most common empirical equation that is used in blasting operations to estimate PPV. As can be seen in Table 1, this equation contains two site constants, K and B, which can be determined by regression analysis. In this section, these constants for Sarcheshmeh copper mine are determined using regression analysis on training datasets in SPSS 16 software. The final form of USBM equation for Sarcheshmeh copper mine is shown below:

$$\mathrm{PPV} = 81.078 \cdot \left[D/Q^{1/2}\right]^{-0.906} \tag{2}$$

6 Performance assessment of models

In this section, performances of constructed models (ANFIS–PSO, SVR, and USBM) are evaluated using 24 blast events (testing datasets), which were not incorporated in the models. Figure 1 and Table 4 show the comparison of predicted PPV values using the ANFIS–PSO, SVR and USBM models and measured (actual) PPV values. It can be seen from Table 2 that the predicted PPV by ANFIS–PSO model is closer to the measured PPV in comparison to the SVR and USBM models. The error range of ANFIS–PSO varies between −5.17 and +2.96, for SVR varies between −5.61 and +3.56, and for USBM varies between −8.77 and +8.41; this indicates that the prediction of PPV using ANFIS–PSO model is more accurate than that of the SVR and USBM models.

To evaluate the accuracy of the mentioned models, two criteria are used: root mean square error (RMSE; Eq. (3)) and variance account for (VAF; Eq. (4)). A predictive model is accepted as excellent when RMSE is 0 and VAF is 100 %.

$$\mathrm{RMSE} = \sqrt{\frac{1}{m}\sum_{i=1}^{m}(A_i - P_i)^2} \tag{3}$$

$$\mathrm{VAF} = \left[1 - \frac{\mathrm{var}(A_i - P_i)}{\mathrm{var}(A_i)}\right] \times 100 \tag{4}$$

where A_i and P_i are the measured (actual) and predicted values of PPV, respectively, and m is the number of blasting event.

Table 6 Main advantages and disadvantages of ANFIS–PSO and SVR

Technique	Advantage	Disadvantage
ANFIS–PSO	Refining fuzzy if–then rules to describe the behavior of a complex system Very fast convergence time	Low accuracy when there are not enough training data Cannot handle multiple output systems Long run time when the number of membership functions is large
SVR	Suitable for problems with limited training data The final results are stable, reproducible, and largely independent of algorithm used to optimize the SVR parameters	High computational burden when the number of data is large, solving the problem becomes difficult Cannot handle multiple output systems

The values of performance indices (RMSE and VAF) for ANFIS–PSO, SVR and USBM models are listed in Table 5. As can be seen, the USBM shows the lowest prediction capacity, whereas two other models can predict PPV with acceptable error rates, but the ANFIS–PSO model exhibits lower error rates than the SVR model.

The coefficient of determination (R^2) between the measured and predicted values is a good indicator to check the prediction performance of each model. R^2 is a positive number that can only take values between zero and one. A value for R^2 close to one shows a good fit of the forecasting model and a value close to zero presents a poor fit. Figure 2 shows the relationship between measured and predicted values, with good determination coefficient, obtained from three predictive models. As can be seen, between developed models, the ANFIS–PSO model shows a higher prediction performance.

The findings of this section reveal that ANFIS–PSO and SVR are efficient and useful techniques for PPV prediction due to bench blasting. These two approaches have some advantages and disadvantages in comparison with each other. The main advantages and disadvantages of these techniques are presented in Table 6.

7 Conclusions

This study proposes a novel hybrid approach based on ANFIS framework, optimized by PSO for estimation of PPV. Tuning parameters of ANFIS formulation were obtained through searching mechanism of PSO which results in an optimized ANFIS model. The application of the ANFIS–PSO model in field of mining and blasting engineering is both novel and effective. The ANFIS–PSO as a soft computing method showed acceptable prediction capacity. The performance of the ANFIS–PSO and SVR models against the USBM model indicated that both intelligent models are suitable and practical techniques and can be used effectively for PPV prediction with acceptable error rates. Furthermore, the comparison of two models revealed that the ANFIS–PSO model was more successful and produced more reliable predictions than the SVR model. Based on testing datasets, the error range of ANFIS–PSO varies between −5.17 and +2.96 and for SVR varies between −5.61 and +3.56. The RMSE, VAF and R^2 values were obtained as 1.83, 93.37 and 0.957 for the ANFIS–PSO, respectively, whereas these values were obtained as 2.40, 89.49, and 0.924 for SVR model.

Finally, it should be noted that the developed models in this study are specific to Sarcheshmeh copper mine. The application of these models directly in other mines is not recommended and some modifications are necessary based on blasting and mining conditions.

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