

# Propagation Prediction and BS Planning for Indoor Wireless Communication

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## Abstract

*The installation of indoor radio systems requires rather detailed propagation characteristics for any arbitrary configuration, so appropriate wave propagation model must be established. In spite of a number proposed solutions for optimal BS stations planning in WLAN environment, it is difficult to say that we have completely satisfied solution. We developed neural network propagation model that was trained for particular environment. The network architecture is based on the multilayer perceptron with two input layers. The neural network results are additionally compared with the numerical results obtained by the deterministic 3-D ray tracing model. The neural network is used to absorb the knowledge about given environment through training with three base stations. Using such obtained knowledge the network is used to predict signal strength at any spot of space under consideration. Therefore, the neural network based propagation model is used as a cost function for optimization of the position of base station. As optimization algorithm it is used particle swarm optimization (PSO) algorithm. The results of PSO are compared with results obtained with two standard algorithms such as simplex optimization method and Powell's conjugate direction method.*

## 1. INTRODUCTION

The popularity of indoor wireless communication systems - phones, hand-held terminals, various PDA devices - are constantly increasing. These portable devices tend to be mobile and in principle can be located anywhere, while base stations need to provide good link to the communications backbone of the system. The base stations need to be positioned carefully so that they cover the building with adequate signal level. Generally problem can be reduced to given building, where we need to answer on questions like how many base stations will be needed, on which positions they will be placed to cover the building with minimum power level.

Prediction of the signal strength for indoor propagation environments is faced with effects of multipath propagation, such as signal attenuation, reflection, diffraction, and interference, due to diversity of building geometrical and construction characteristics [1],[2],[3],[4]. The Maxwell's equations with the relevant boundary conditions enable the most accurate solving indoor propagation problems, but with extreme calculation complexity. To avoid this complexity a lot of empirical propagation models have been developed. The ray tracing model based on geometric optics is enough accurate when include more than one reflected ray, and also diffraction effects. This model requires detailed information about building characteristics and too much computation time, so it can't be feasible for real buildings.

Artificial neural networks can be used as an alternative to various deterministic propagation prediction methods. Several authors have already

proposed such solutions [5], [6] with different approaches and neural network architectures. Very good input-output mapping make these networks useful in signal strength prediction with the same accuracy as other deterministic methods. Through the learning process the relevant network has possibility to absorb the knowledge about propagation characteristics for given indoor space, based on the relationship between input and output. The network is trained with measured data, and tested with different data, also obtained by measurement. Additionally, the adequacy of using neural networks in indoor propagation prediction problems is proved by comparison with ray tracing results. The main task of the neural network was to determine appropriate values of cost function that is used in the base station optimization process. The relevant network architecture is trained for determining receiving signal on randomly distributed locations from three base stations located on different places. As this neural network model showed very good generalization characteristics, it is used to produce relevant values of cost (objective) function for coverage and interference limited environments. We utilize the penalty function approach. The accuracy of the cost function is critical for usefulness of our approach, so the propagation and fading environment need to be correctly modeled.

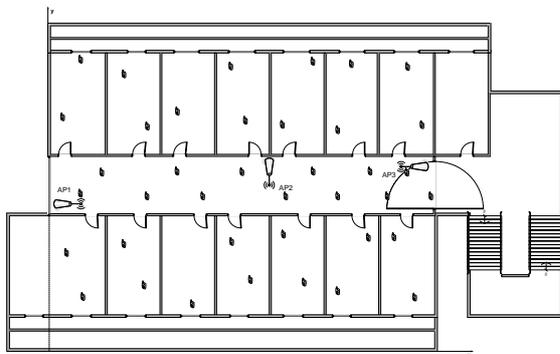
Different optimization methods are used for determining the optimum locations for the base stations that must meet a given performance criteria. The unconstrained optimization techniques are chosen according to the penalty function approach. The results of the downhill simplex method, Powell's conjugate direction method and

Particle Swarm Optimization (PSO) algorithm are compared. First mentioned two methods are well known methods for numerical multidimensional optimization that don't require derivatives of the cost function [7]. PSO has been presented as effective method in optimizing complex multidimensional problems. Specially, successful application of this method to antenna design has been shown [8], [9]. In our case, we were faced with multiple local optima. The problem is overcome by fine tuning the parameters of the each optimization algorithm.

The paper is organized as follows. In section 2 the propagation model is presented with geometry of the environment under consideration and neural network model with results in propagation prediction. The way how we obtained cost function is clarified in section 3. Optimization algorithms are introduced in section 4, while optimization results are presented in section 5. Finally, section 6 consists of some conclusion remarks.

## 2. PROPAGATION MODEL AND NEURAL NETWORK

The second floor of Dubrovnik University B building is chosen for simulation environment. The dimensions of the floor are  $33 \times 11 \times 2.40 \text{ m}^3$ , as it is shown in Fig. 1 with origin of coordinate system in left lower corner and locations of base stations for neural network training purposes. The environment



**Fig. 1.** Plan of the second floor university building

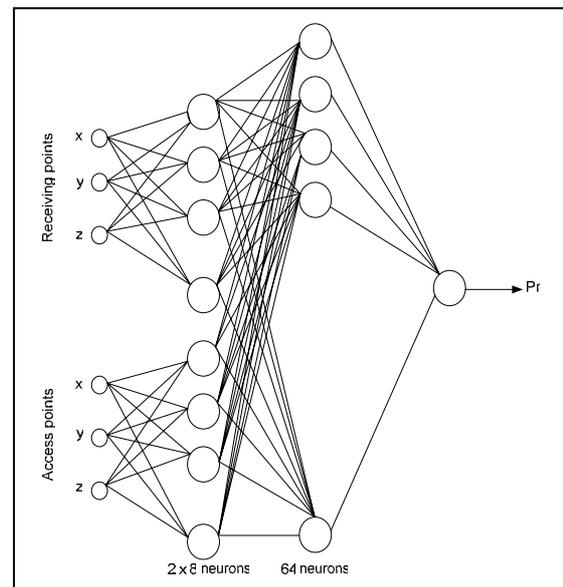
under consideration ends with folding door. The access points are CISCO Aironet 1100 series for WLAN 802.11b standard. Coordinates of base stations are shown in the Table 1. The walls are made of the bricks with wooden doors, while the ceiling and floor are made of the concrete.

Measurements of the received signal strength for the various locations of the receiver and each base station (Fig.1) have been made in the first step. The each WLAN access point was operating on the 7<sup>th</sup> channel at 2.437 GHz (100mW), and transmitter antenna gain was 8.5 dBi. The signal strength measurements were made by a laptop computer

with PCMCIA wireless card positioned 1.2 m above the floor. The measurements were performed for 98 receiving points (locations) that were 1 m apart from each other. There were made three measurements for each location and mean value was saved with location coordinates. These values will be used in the training and testing of the neural network.

Base station	x	y	z
AP1	0.0	4.85	2.2
AP2	17.0	7.65	2.2
AP3	33.0	7.65	2.2
AP5	30.0	2.3	2.2

**Table 1.** The Coordinates of base stations

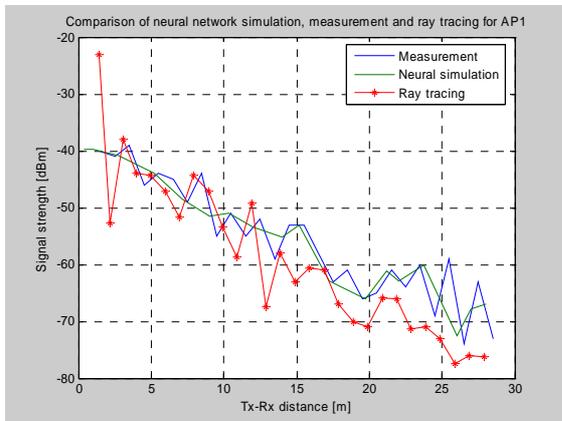


**Fig. 2** Neural network architecture

According to the recommendations from [10] we chose multilayer perceptron (MLP) for propagation simulation that is shown in the Fig. 2 with two input layers and two hidden layers. The input layers as inputs receive location coordinates of base stations and receiving points. The network has one neuron in output layer for relevant signal strength value. Such neural network architecture can be learned applying a set of labeled training samples that involve modification of the synaptic weights of neural network to produce corresponding (desired) output [10]. The training of the network is repeated for many input samples until the network reaches a steady state where there are no significant changes in the synaptic weights. After training phase the neural network is tested or simulated with input data from the set of examples but different of that used in the training, and if the outputs are reasonable the network generalizes well.

Appropriate initial values of synaptic weights (also called free parameters) and learning algorithm are crucial for learning phase, after the architecture of the network has been determined. As training rule we chose algorithm that updates the weight and bias values according to Levenberg-Marquardt optimization [11]. It minimizes a combination of squared errors and weights, and then determines the correct combination so as to produce a network that generalizes well. The process is called Bayesian regularization [11]. Activation function is of sigmoidal type except for the output layer where it is linear function.

As it is visible in the Fig. 1 base stations AP1, AP2, and AP3 are chosen for training and testing of the network. Randomly are determined 78 receiving locations for training purpose and 20 for network testing of the total number of 98 receiving locations for which the measurement have already been made (Fig. 1). This has been made for each base station that for training results in 78x3 pairs of receiver coordinates - signal strength and 20x3 such groups for testing. Good network generalization is shown in the Fig. 3, where the change in signal strength with increasing transmitter-receiver separation is shown for neural network model, ray tracing calculation, and measured data. The differences between measured, simulated and calculated results are more significant in the proximity of the transmitter.

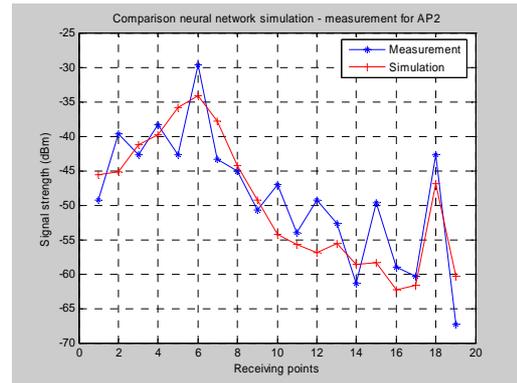


**Fig. 3** Comparison of neural network simulation, measurement and ray tracing for base station AP1 and receiving points in main corridor

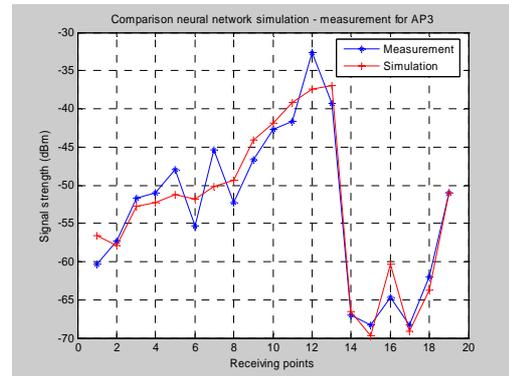
Neural network simulation results for base stations AP2 and AP3 are shown in Fig. 4 and 5 respectively. Receiving points denoted with numbers from 1 to 12 are located in main corridor, with beginning at  $x = 0$ , while the receiving points denoted with numbers from 13 to 20 are located in different rooms. We can see acceptable matching between neural network simulation results and measurement data for various testing locations of receiver according to the Fig. 1. The overall mean

variation of neural results in comparison with measured data was 3.8 dBm.

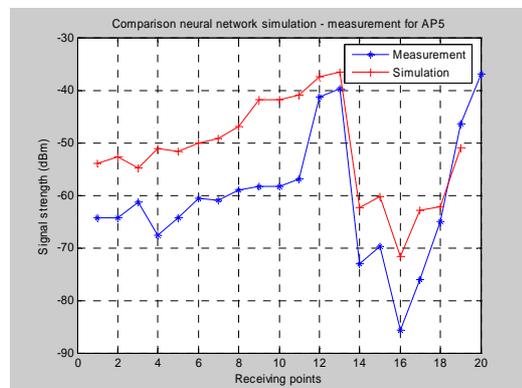
Additional testing is performed for base station AP5, that is not been participating in the training of the network. It is located at (30, 2.3) coordinates and results of comparison with measured data are shown in the Fig. 6. This is the worst case, so the mean variation between neural and measured data was little bit less than 10 dBm. In spite of this not encouraging result, we think that this method is still usable.



**Fig. 4** Comparison of neural network simulation and measurement for base station AP2



**Fig. 5** Comparison of neural network simulation and measurement for base station AP3



**Fig. 6** Comparison of neural network simulation and measurement for base station AP5

### 3. A COST FUNCTION BASED ON NEURAL NETWORK PREDICTION

In order to find optimal location of a single transmitter for a given distribution of receivers, we need to develop a numerical representation for the quality of signal coverage over the given space as a function of the transmitter location. To obtain such function we need to partition given space into grid of possible receiver and transmitter locations. The density of the grid is determined by the desired accuracy. The trained neural network is used to determine signal level on any receiver location wherever base station was located. According to such approach cost function is presented as sum of all weighted relative signal level predictions (-dBm) along with a penalty value that represents a violation in a maximum tolerated path loss threshold at receiver location, what in our case was receiver threshold (-86dBm). The cost function, then, can be expressed as

$$f_i = -\sum_{i=1}^N \sum_{j=1}^M S_i(x_j, y_j, z_j) w(S_i(x_j, y_j, z_j)) \quad (1)$$

where  $N$  and  $M$  are the number of possible locations of base stations and receiving points respectively.  $S_i$  is relative signal level (dBm) received from base station  $i$  at location with coordinates  $x_j, y_j$ , while  $w_j$  is relevant priority weight ascribed to the  $j$ th receiver location, and it makes constraints in cost function. This constraint requires that the quality of signal coverage at each receiver location over a given space must be above a given threshold value (-86 dBm). In precise case the value of weight  $w_j$  is obtained as

$$w_j = \begin{cases} S_i(x_j, y_j, z_j) > -60dBm & w = 1 \\ -60 \geq S_i(x_j, y_j, z_j) \geq -86dBm & w = 10 \\ S_i(x_j, y_j, z_j) < -86dBm & w = 100 \end{cases}$$

The cost function as a function of three variables ( $x, y, z$ ), that represent location of base station, is calculated according above rules where relevant signal levels are obtained from neural network trained model. For given grid of base stations and receiver locations this function has graphical shape presented in Fig. 7. The coverage is not smooth or differentiable function of the base station locations, so received signal strength may exhibit discontinuities because very little change in base station location can cause great change in received signal strength that is caused by completely different pattern of reflected, transmitted and diffracted rays. We need to expect a lot of such discontinuities in real buildings.

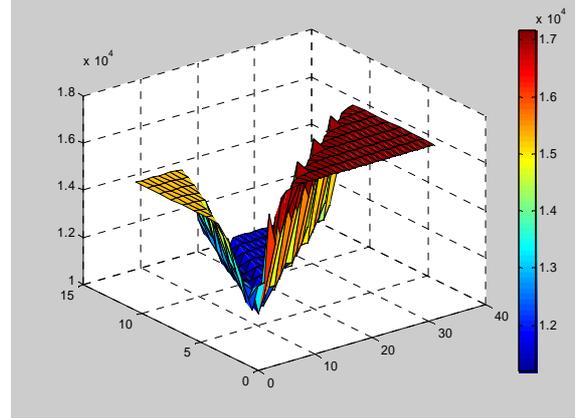


Fig. 7 3-D graphical presentation of cost function

The mentioned reasons make such cost function extremely limited in accuracy when it is calculated for limited number of grid points. As in our method the cost function is calculated from neural network propagation model there are no limits in grid points i.e. the received signal strength can be calculated for any point in the given space in optimization process. The optimization process is performed through the searching minimum of cost function. We used three different methods in optimization process that will be described in next sections.

## 4. OPTIMIZATION

### 4.1 Direct Search Methods

As presented cost function incorporates constraints unconstrained optimization technique will be used. The described characteristics of cost function determine which optimization procedure will be the most appropriate, and according to that we should use an optimization method that is not gradient based. Such algorithms are known as direct search methods. Here we consider two of them the Simplex Search method [7] and Powell's conjugate direction method [7]. Actually, we used the results of these two methods for comparison with the result of the Particle Swarm Optimization (PSO) algorithm [8].

The Simplex Search method is an evolutionary optimization approach that starts with initial simplex which is a polyhedron of  $n+1$  vertices where  $n$  is the dimension of the problem [7]. Powell's conjugate direction method provides optimization of a general  $n$ -dimensional quadratic objective function through  $n$  searches [7]. The important aspect of optimization algorithms is how well they can handle multiple local minima, because we expect many local minima in our cost function as consequence of the propagation environment. The technique of Simplex Search method is less susceptible to the local minima

problem then Powell's conjugate method. It is impossible to overcome this problem completely. There is possibility to restart optimization procedure with an alternative initial position and run algorithm again to verify are the same optimum values achieved.

The coordinates of base station through the optimization process in the case of the Simplex Search method are shown in the Fig. 8 with the final optimal result. Very similar result we obtained also with Powell's conjugate method ( $x = 11.61, y = 7.17, f = 1.1154 \cdot 10^4$ ).

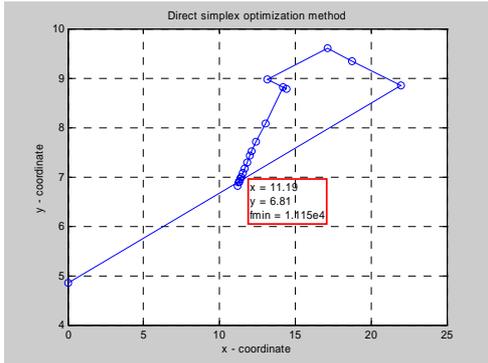


Fig. 8. Direct Simplex Search Method

#### 4.1 Particle Swarm Optimization (PSO) Algorithm

There a number of papers that show how PSO is effective in optimizing difficult multidimensional problems. The PSO algorithm has a swarm composed of multi-particles according to its name. Each particle has its own position and velocity in the space under consideration. Particles from random places with random velocities look for better or best value of objective function than it is current one. Particles exchange information about results they obtained, so they know the best of all results so far. According to this information they accelerate in the direction of the global best result ( $gbest$ ) and in the same time toward its own best result ( $pbest$ ), so their trajectory is altering between these two goals depending what direction prevails. On such way they explore entire space to be pulled to the point that gives better result, and finally this movement can lead them to the place with global best result. Soon, all the particles will be gathered around this point.

The PSO, although originally invented for research on simulating the movement of the swarm in 2-dimensional space, as an optimization method can be applied in  $n$ -dimensional space [9]. The particles are defined with its own position  $x$  and velocity  $v$ , and it also has its personal best result so far ( $pbest$ ). The key element of the entire optimization is the changing of particle's velocity [5]. For the  $k+1$  particle movement, the  $j$ -th

coordinate component of velocity  $i$ -th particle, we can write for the particle velocity

$$v_{ij}^{k+1} = c_0 v_{ij}^k + c_1 rand_1 (pbest_{ij} - x_{ij}^k) + c_2 rand_2 (gbest_{ij} - x_{ij}^k) \quad (2)$$

In above equation  $i = 1, 2, \dots, m$ , where  $m$  is the size of the swarm;  $j = 1, 2, \dots, n$ , where  $n$  is dimension of the space;  $c_0, c_1$ , and  $c_2$  are positive constants that scale the old velocity and increase new velocity toward  $pbest$  or  $gbest$ , respectively.  $rand_1$  and  $rand_2$  represent random number that is uniformly distributed in interval  $[0,1]$ . The parameter  $c_0$  is called "inertial weight" and it determines does the particle will stay on its current trajectory or it will be strongly pulled toward  $pbest$  or  $gbest$ . Its value is between 0 and 1. The new particle location is given by

$$x_{ij}^{k+1} = x_{ij}^k + \Delta t v_{ij}^{k+1} \quad (3)$$

The new velocity is applied for some time-step  $\Delta t$ , which is usually one.

A proper selection of parameter values is very important to obtain qualitative result. We can find different proposals for inertial weights and other constants in articles of various authors. Considering suggestions of several authors and experimenting PSO algorithm with different parameters we got best result when inertial weight  $c_0$  was changed linearly from 0.9 to 0.2 during the run of algorithm. On this way we got that in the beginning of the algorithm run particle is less pulled toward  $pbest$  and  $gbest$ , but after a number of iterations they are more rapidly pulled toward these values, what illustrates Fig. 9 for three different values of  $c_0$ . Higher value of  $c_0$  means faster move toward  $gbest$ , faster convergence, but less accuracy.

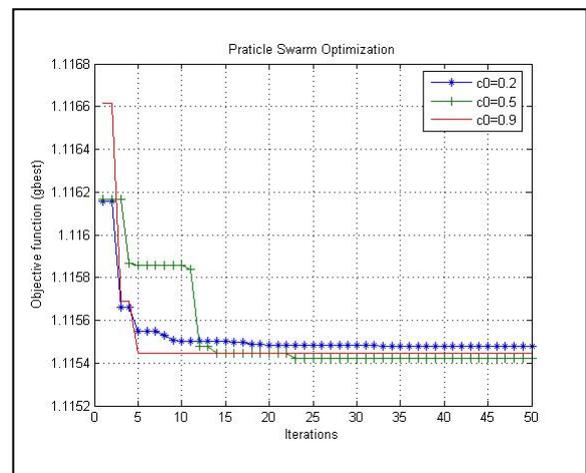


Fig. 9 Cost function for different inertial weights

For the constants  $c_1$  and  $c_2$ , value of 2 is used, but in our case where very little change in coordinates may result in great change in cost function value, the time step needs to be chosen carefully. Considering chosen values for  $c_0$ ,  $c_1$ ,  $c_2$  and examining equations (2) and (3) for time step value we chose 0.4.

We carefully selected population size among large populations with a lot cost function evaluations and longer computation time, and smaller populations that give results much faster. It was determined by many parametric studies [9] that relatively small populations can sufficiently explore our space under consideration, so population of 30 particles is used in our algorithm.

The particles can move beyond the boundaries of the given space, so it is desirable to limit the search to the space of interest. This is obtained by boundary conditions that determined what to do when the particle is moved out of the given space. Among the three possible boundary conditions introduced by various authors we chose so called "reflecting walls" [9]. When particle hits the space boundary in one of dimensions, reflecting walls act so that the sign of particle velocity in that dimension is changed and particle is reflected back to the space of interest, by the rules of total reflection. As it was showed [9] what type of boundary condition to utilize is highly dependent of cost function. For our cost function reflecting walls are little bit more difficult for programming, but affect with more accuracy on the result.

## 5. OPTIMIZATION RESULTS

The computer programs for considered three optimization methods and cost function evaluation have been developed. It is necessary to emphasize that the accuracy of final results depends on accuracy of the signal strength estimation obtained by described neural model.

The results are presented in the Table 2.

Simplex			Powell			PSO	
n	starting points	Result	n	Starting point	Result	n	Result
160	0, 485	11.19	59	0, 4.85	11.62	50	11.34
	0, 20.85	6.81			7.17		6.94
	16, 4.85	2.2			2.2		2.2

**Table 2.** Optimization results obtained by three methods

The  $n$  in Table 2 denotes number of evaluations of cost function during algorithms run, while other data are relevant coordinates. As a *simplex* is the geometrical figure consisting of four points (number of dimensions + 1) [7] it is need to have four starting points that can be obtained as

$$P_i = P_0 + \lambda e_i \quad (4)$$

where  $P_0$  is initial starting point (0, 4.85, 2.2),  $e_i$ 's are unit vectors, and  $\lambda$  is a constant that defines length scale (16 in our case). We want to fixed third coordinate to 2.2, so we our problem reduced to 2-dimensional problem as it is shown in the table 2. The initial point in the Powell's method is located at the left boundary of the given space.

All three methods give very similar results. Experimental verification confirmed our findings. The PSO algorithm shows better performance than two other, what is manifesting in less iterations and higher accuracy according to the experimental verification. The optimal result obtained by PSO algorithm is between two others, but all three satisfy coverage requirements. It must be noticed that obtained optimal coordinates don't cover with geometrical center of space under consideration (16.5, 6.5), but it is not very far from it (Fig. 1).

## 6. CONCLUSION

The contribution of the research presented in this paper is that we incorporate a lot of propagation phenomena and optimization of base station location without complex and long last computations with practically equal accuracy as it is with more deterministic methods. The neural network model is shown as very good method for cost function evaluation, because the grid of receiving points (arguments of the function) can be unlimited dense, what contributes to the accuracy of the result. Very short overview is given for Particle Swarm Optimization algorithm. Also, it is presented how the parameters for this algorithm are selected. Finally, the optimization of three methods is compared. The presented model can be used for refinement of existing indoor networks and it can be a good tool for network planning in general.

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