Mobile Position Estimation using Artificial Neural Network in CDMA Cellular Systems

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ABSTRACT

Using the Neural network as a type of associative memory will be introduced in this paper through the problem of mobile position estimation where mobile estimate its location depending on the signal strength reach to it from several around base stations where the neural network can be implemented inside the mobile. Traditional methods of time of arrival (TOA) and received signal strength (RSS) are used and compared with two analytical methods, optimal positioning method and average positioning method. The data that are used for training are ideal since they can be obtained based on geometry of CDMA cell topology. The test of the two methods TOA and RSS take many cases through a nonlinear path that MS can move through that region. The results show that the neural network has good performance compared with two other analytical methods which are average positioning method and optimal positioning method.

Keywords: feed forward neural network, time of arrival, received signal strength, back propagation, optimal positioning method, and average positioning method.

تقدير موقع الهاتف المحمول بأستعمال الشبكة العصبية الصناعيـة في أنظمة CDMA الخليويـة

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الخلاصة

ان استعمال الشبكات العصبية كنوع من الذاكرة المترابطة سيطرح ضمن هذا البحث من خلال تقديم مشكلة تقدير موقع الهاتف المحمول حيث ان الهاتف سيقوم بتقدير موقعة بالاعتماد على شدة الاشارة المستلمة من قبل عدة محطات مجاورة له حيث ان الشبكة العصبية ممكن ان تبنى داخل الهاتف. استخدمت طرق تقليدية مثل طريقة زمن الوصول وطريقة قوة الاشارة المستلمة وتمت مقارنتها مع طرق تحليلية و هي طريقة المعدل والطريقة الفضلى. وكانت البيانات التي استخدمت في تدريب الشبكة مثالية اعتمدت من التصميم المعتمد ضمن النظام الخليوي للCDMA ثم تم اختبار هذه الشبكة على مسار تم تحديده ضمن منطقة معينة ومقارنة نتائج الشبكة مع الطريقتين التحليليتين.

كلمات رئيسة: التغذية الامامية للخلايا العصبية، زمن الوصول، شدة الاشارة المستلمة، الانتشار العكسي، الطريقة المثلى لتحديد الموقع، طريقة المعدل لتحديد الموقع.

1. INTRODUCTION

Mobile positioning consider as an essential application nowadays mobile station (MS) position may be found with assistant of cellular network that mean network-based techniques or by using GPS and this mean hand set- based techniques the purposes and methods that found for MS location estimation are many some of purposes are for security and for emergency calls and other for services. About methods researchers and authors use these methods theoretically or by simulation or empirically the aim of the paper are to explain how to develop the feed forward neural network as an associative memory for purpose of MS positioning through simulation using matlab. Considering the importance of mobile positioning in daily life applications many techniques and methods were proposed that depend on signal transmitted between MS and BS. Some of these methods are hand set based methods and the other are network based methods, **Karray** and **Silva, 2004.** The common methods used in mobile positioning are time of arrival (TOA), received signal strength (RSS) and angle of arrival (AOA). All of them depend on the radio signal travelling between MS and BS. The idea began when three points which represent base stations BS centered each cell of CDMA have known. Fixed position three circles will be formed when taking appoint of MS with three BSs. The position of MS will be the intersection of these circles, but due to NLOS error that affects the signal, the intersection point will be an uncertainty region and the aim is to find MS position inside this region. **Cong,** and **Zhuang, 2002**, Proposed a scheme that combined the time difference of arrival (TDOA) measurements from the forward link pilot signals with the angle of arrival (AOA) measurement from the reverse link pilot signal. A two-step least square location estimator was developed based on a linear form of the AOA equation in the small error region. **Chen, et al., 2010**, illustrated hybrid proposed schemes that combine time of arrival (TOA) at three BSs and angle of arrival (AOA) information at the serving BS to give location estimate of the MS. The proposed schemes mitigate the NLOS effect simply by the weighted sum of the intersections between three TOA circles and the AOA line without requiring a *priori* information about the NLOS error. **Ping, et al., 2006**. The model of the data fusion with multi-parameters of TOA/TDOA/AOA is set up to optimize network hybrid location, and the inaccuracy or fuzzy problem produced by conventional location algorithm can be overcome effectively, **Sheen, et al.,2002.** An adaptive fuzzy logic estimator for locating mobiles in a direct sequence code division multiple access (DS/CDMA) cellular system is proposed. The location estimation is based on the measured pilot signal strengths by the mobile station (MS) from a number of nearby base stations (BSs). A smoother, which uses past and current output data from the fuzzy estimator to produce a more accurate estimate, is used to improve the accuracy of the location estimation. In **Caffery,** and **Stuber, 1998,** two methods are considered measured times of arrival (TOA) and angles of arrival (AOA). The TOA measurements are obtained from the code tracking loop in the CDMA receiver, and the AOA measurements at a base station (BS) are assumed to be made with an antenna array. **Venkatraman, et al., 2004,** proposed a location technique that estimates the line-of-sight (LOS) ranges based on NLOS range measurements. The approach utilizes a constrained nonlinear optimization approach for range measurements available from three base stations. The constraints were extracted from bounds on the NLOS error and the relationship between the true ranges. A hybrid location scheme, presented by, **Chen,** and **Feng, 2005**, which combined the satellite-based and the network-based signals, the proposed scheme utilizes the two-step Least Square method for estimating the three-dimensional position (i.e. the longitude, latitude, and altitude) of the mobile devices. The Kalman filtering technique was exploited to both eliminate the measurement noises and to track the trajectories of the mobile devices. A fusion algorithm was employed to obtain the final location estimation from both the satellite-based and the network-based systems. **Zhou, et al., 2009**, designed a directional propagation model, the Modified Directional Propagation Model (MDPM), which makes use of a common signal propagation model to perform location estimation. It is a signal strength based algorithm which estimates the location of the Mobile Station by signal strength received from the nearly base stations. **Wei,** and **Lenan, 2009,** presented a mobile station location method using constrained least-squares (CLS) estimation in the non-line of sight (NLOS) conditions. When some of the measurements are from NLOS paths, the location errors can be very large. The proposed method mitigates possible large TOA error measurements caused by NLOS. The memorization capability of a multilayer interpolative neural network in, **Abdlwahhab, 2014** is exploited to estimate a mobile position based on three angles of arrival. The neural network is trained with ideal angles-position patterns distributed uniformly throughout the region. In **Chen,** and **Lin, 2011** a novel algorithm was proposed that combines both time of arrival (TOA) and angle of arrival (AOA) measurements to estimate the MS in NLOS environments. The proposed algorithm utilizes the intersections of two circles and two lines, based on the most resilient back-propagation (Rprop) neural network learning technique, to give location estimation of the MS. The traditional Taylor series algorithm (TSA) and the hybrid lines of position algorithm (HLOP) have convergence problems, and even if the measurements are fairly accurate, the performance of these algorithms depends highly on the relative position of the MS and BSs. Different NLOS models were used to evaluate the proposed methods.

2. PAPER ORGANIZATION

This paper is organized as follows. After a brief review on the nature of the work of the paper and some of related works in the same field the structure of the neural network used would be presented in section two that network used to find the position of the mobile inside the CDMA cellular system which described in section three and compared the network design with two other methods which are average positioning method that described in section four while section five talked a bout the other method which is optimal positioning method section six shows how to train the network using the generated pattern where section seven shows how to calculate this pattern uniformly (any generated pattern can be used) the results of testing the network would be shown in the section eight finally conclusions were obtained through the period of the work would be presented in section nine.

3. ARCHITECTURE OF NUERAL NETWORK

The architecture of NN consist of three layers, input layer with three neurons that represent measurements received from three base stations and a single hidden layer with forty neurons and unipolar sigmoid as activation function and output layer of two neurons that represent position of mobile station with linear activation function. As shown in **Fig.1.**

Where S= $[s_0\ s_1\ s_2]^T$ input of the neural network.

O=$[x\ y]^T$ output of the neural network.

V_{ji}= 40 * 4 the hidden layer weight matrix with bias.

W_{kj}= 41 *2 the output layer weight matrix with bias.

4. THE PROPOSED CELLULAR SYSTEM LAYOUT

A two dimensional model of a CDMA cellular system was assumed. Where the area is divided into contiguous cells each cell is served by a single base station as shown in the **Figs. 2 and 3**.

5. AVERAGE POSITIONING METHOD

It is an analytical method in which intersection of three circles centered by base station can be shown in **Fig. 5** and found mathematically as

a. Intersection of circle of BS_0 and circle of BS_1

$$X_A = \frac{\left(0.5 * (y_1 - y_0) * (d_0^2 - d_2^2 + x_2^2 - x_0^2 + y_2^2 - y_0^2) - 0.5 * (y_2 - y_0) * (d_0^2 - d_1^2 + x_1^2 - x_0^2 + y_1^2 - y_0^2)\right)}{\left((x_2 - x_0) * (y_1 - y_0) - (x_1 - x_0) * (y_2 - y_0)\right)} \quad (1)$$

$$Y_A = (0.5 * (d_0^2 - d_1^2 + x_1^2 - x_0^2 + y_1^2 - y_0^2) - (x_1 - x_0) * X_A)/(y_1 - y_0) \quad (2)$$

b. Intersection of circle of BS_0 and circle of BS_2

$$X_B = \frac{\left(0.5*(y_1-y_0)*(d_1^2-d_2^2+x_2^2-x_1^2+y_2^2-y_1^2)-0.5*(y_2-y_1)*(d_0^2-d_1^2+x_1^2-x_0^2+y_1^2-y_0^2)\right)}{\left((x_2-x_1)*(y_1-y_0)-(x_1-x_0)*(y_2-y_1)\right)} \quad (3)$$

$$Y_B = (0.5 * (d_0^2 - d_1^2 + x_1^2 - x_0^2 + y_1^2 - y_0^2) - (x_1 - x_0) * X_B)/(y_1 - y_0) \quad (4)$$

c. Intersection of circle of BS_1 and circle of BS_2

$$X_C = \frac{\left(0.5*(y_2-y_0)*(d_1^2-d_2^2+x_2^2-x_1^2+y_2^2-y_1^2)-0.5*(y_2-y_1)*(d_0^2-d_2^2+x_2^2-x_0^2+y_2^2-y_0^2)\right)}{\left((x_2-x_1)*(y_2-y_0)-(x_2-x_0)*(y_2-y_1)\right)} \quad (5)$$

$$Y_C = (0.5 * (d_0^2 - d_2^2 + x_2^2 - x_0^2 + y_2^2 - y_0^2) - (x_2 - x_0) * X_C)/(y_2 - y_0) \quad (6)$$

The average point will be

$$X_{MS} = \frac{X_A + X_B + X_C}{3}$$

$Y_{MS} = \frac{Y_A + Y_B + Y_C}{3}$ and the position of this method will be (X_{MS}, Y_{MS})

6. OPTIMAL POSITIONING METHOD

This method finds mobile station (MS) location by minimizing the sum of squares of a nonlinear cost function. If the mobile has the position (x_0,y_0) and transmit a signal at time t_0, *n* number of base stations will be found to receive this signal. The base stations (BS's) positions are (x_1,y_1),

(x_2,y_2), ……,(x_N,y_N) and receive the signal at time t_1, t_2, …., t_N. as in, **Liu, et al., 2007.**The cost function is represented by Eq. (7):

$$F(x) = \sum_{i=1}^{N} \alpha_i^2 \; f_i^2(x) \tag{7}$$

Where α_i the reliability of signal received at measuring unit.

And $f_i(x)$ is

$$f_i(x) = c(t_i - t) - \sqrt{(x_i - x)^2 + (y_i - y)^2}$$

Where c is speed of light. Finding the values of x, y and t that make $f_i(x)$ equal to zero**.**

7. TRAINED NEURAL NETWORK

NN is trained with online backpropagation algorithm where the weight of the hidden layer designated by V and weight of output layer designated by W were initialized in a random manner with values between -0.5and 0.5. These weights are updated when each input pattern is presented to the NN. The stopping criteria depend on the value of root mean square error (RMS) error defined by Eq. (8).

$$E_{RMS} = \sqrt{\frac{1}{P}\sum_{i=1}^{P}(d^{(i)} - o^{(i)})^T(d^{(i)} - o^{(i)})} \tag{8}$$

Where:

P is the number of training patterns,

$\boldsymbol{d}^{(i)}$ is the i 'th desired value for the output of the neural network.

$\boldsymbol{o}^{(i)}$ is the i 'th actual output of the neural network.

Figs. 5, 6, 7 and 8, show the final steps of learning process that the network is trained because each time oscillation occurs, learning process must be stopped and less the learning rate value and retrain the network in a convergence manner. For time of arrival method different number of neurons in the hidden layer are experimented to reach a value of RMS equal to 12.

Figs.9, 10, 11, 12, 13 and 14, show the final steps of learning process that the network was trained because each time oscillation occurs, learning process must be stopped and less the learning rate value and retrain the network in a convergence manner. For received signal strength method different values of σ and k are used to train the neural network for different propagation environments.

7. GENERATION OF TRAINING PATTERNS

Based on geometry of CDMA cell topology there will be a triangle form from the location of three base stations. Many points inside this region can be found randomly or according to a mathematical algorithm where the position of three BSs are known and value of R (radius of cell) and h (height of cell) are known in this paper a uniform distribution of training patterns used to train the network, these points can be calculated as:

$$x = \frac{3R}{2n_x} \times i \qquad \text{where } i = 0, 1, \ldots, n_x$$

$$y = y_{min} + \frac{y_{max} - y_{min}}{n_y} \times j \quad \text{where} \quad j = 0, 1, \dots, n_y$$

Where n_x and n_y are the number of subintervals on the $x-$ axis and y−axis, respectively.

8. SIMULATION RESULTS AND DISCUSION

The performance of the previously trained neural networks was compared with two conventional methods to find the mobile location, namely the average position method and the optimal position method using Matlab R2010a. The testing points can be individual points or paths choose randomly or described by mathematical representation. In this paper the parabolic path represented by the Eq. (9) and shown in **Fig.13** used to test the performance of the trained neural network.

$$y = 300 + x - 0.0027x(x - 200) \tag{9}$$

The comparisons of the neural network with other analytical methods were illustrated in the **Figs.16-22** for different environment situations, the **Fig. 16** illustrates how the NN even with smaller number of neurons overcome the two other methods especially when error in the signal increase also the figure illustrate that NN with higher number of neurons has better performance. The **Fig. 17** shows that the NN is better than the two other methods this is clearly shown from the linear behavior of the NN with increasing the error when kind of environment situation represented by the values of $k = 2$ and $\sigma = 2$. **Fig. 18** shows that the NN still on the same behavior while other two methods show bad results. **Fig. 19** shows again the good performance of the NN over the two other methods.In **Figs. 20, 21 and 22** illustrate that the NN shows less performance in worse environment but still better than other methods. The model which is used in the work is log normal shadowing and its equation in dB is:

$$PL(d)[dB] = PL(d_0) + 10\,k\log\left(\frac{d}{d_0}\right) + X_\sigma$$

Where σ is the standard deviation and k is path loss exponent which are the important factors of the equation that statistically describe the path loss so that the value of k depend of a specific propagation environments for example free space equal to 2 and have larger values when obstruction are presented that mean better results obtained with lower values of k as cleared in **Theodore S. Rappaport, 2001**.

9. CONCLUSION

a. When there is no error in the measured signal characteristics, the direct analytical methods (such as average position and optimal position methods) give exactly the actual position of the mobile station while the trained neural network approximates the mobile position with some error.

b. In the presence of measurement error (due to NLOS and noise) the performance of the analytical methods begins to degrade because of the presence of the region of uncertainty while the neural network begins to exploit its memorization and generalization capabilities to handle this region. Therefore, as the percentage error of the distance measurements increases, the neural network begins to outperform the analytical methods.

c. A single hidden layer NN is capable of estimating the mobile location

d. The performance of the neural network to find location based on the time of arrival method is better than that of signal strength method because the distance obtained from time of arrival method can be calculated due to linear equations while in signal strength method it obtained from nonlinear equations.

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Nomenclature List

S=input of the neural network.

O=output of the neural network.

d_i=distance between MS and BS_i, m.

c=speed of light, m/μsec.

t_i=time that signal takes from BS_i to MS, μsec.

V_{ji}=connected weights between input layer and hidden layer.

W_{kj}= connected weights between hidden layer and output layer.

α_i= the reliability of signal received at measuring unit.

E_{RMS}= root mean square error value, m.

x_i=position of BS_i in x-axis.

y_i= position of BS_i in y-axis.

σ=standard deviation ranging from 2 to 6 db.

k= The exponent k is dependent on the propagation environment and varies between 2 and 6.

$\delta_{(k)}$=error signal of output layer of neural network.

$\delta_{(j)}$=error signal of hidden layer of neural network.

R=the radius of the cell, m.

h=is the height of the cell, m.

y_{min}=is the lower line of the triangular region of three BSs used in the scheme.

y_{max}=is the upper line of the triangular region of three BSs used in the scheme.

P=is the number of training patterns.

$d^{(i)}$=is the i 'th desired stored response.

$o^{(i)}$=is the i 'th actual output

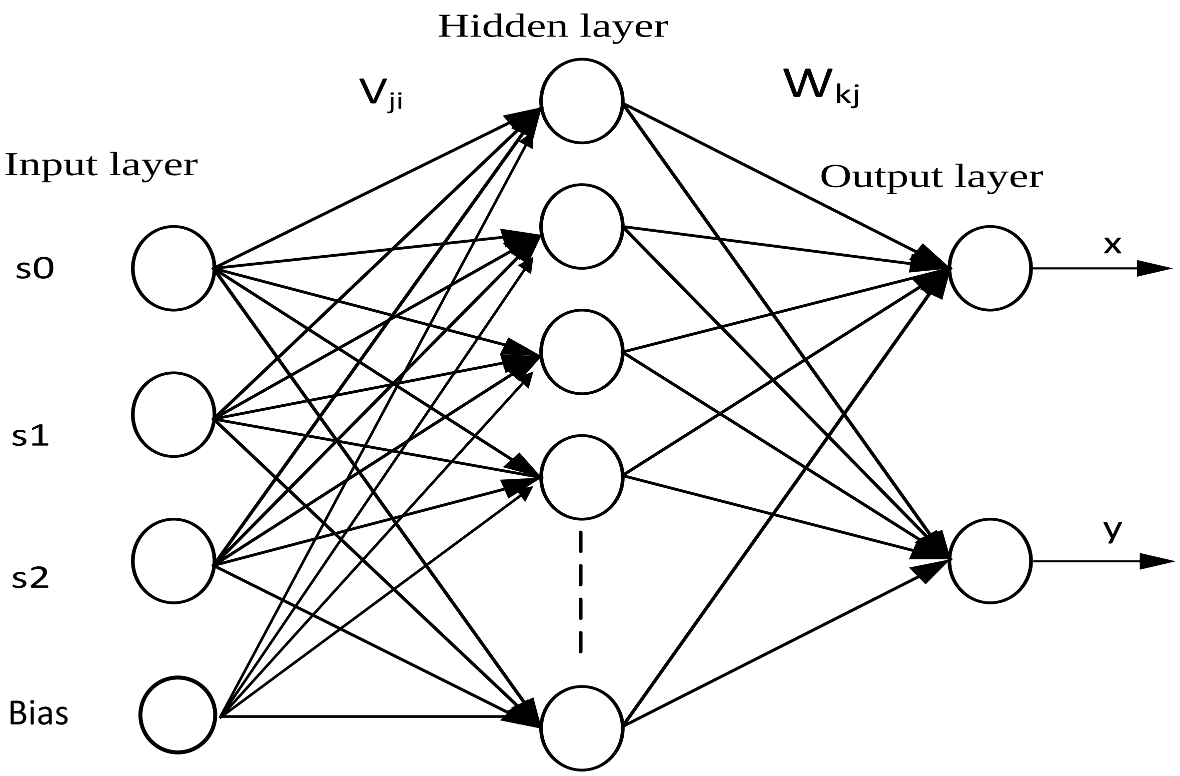

Figure 1. The architecture of the neural network.

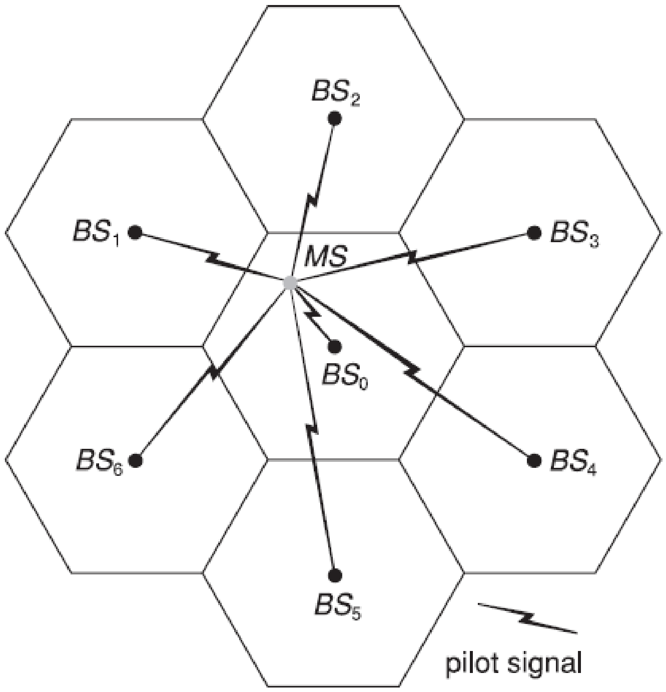

Figure 2. CDMA cellular topology.

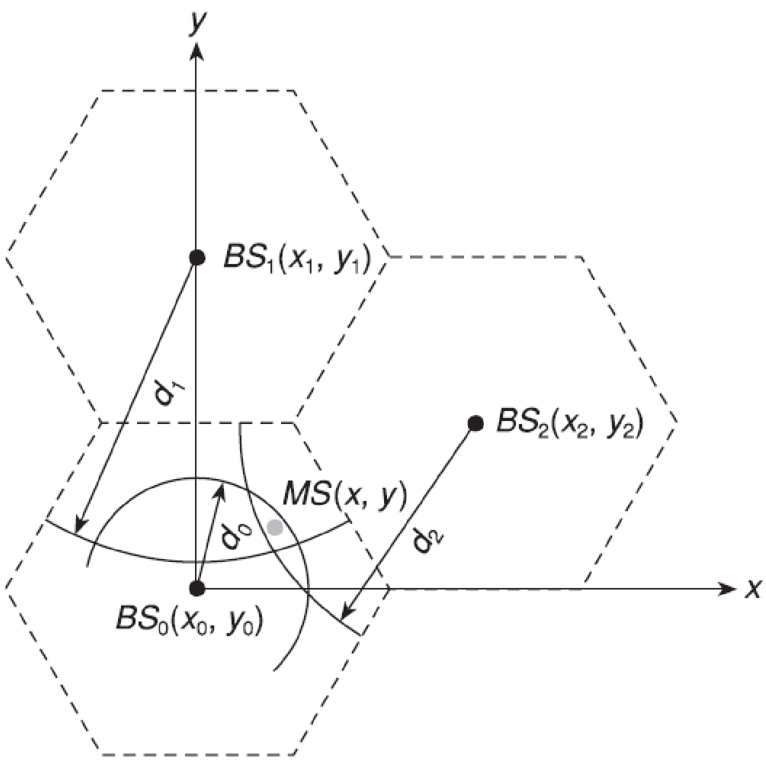

Figure 3. The lateration methods (time of arrival and signal strength**).**

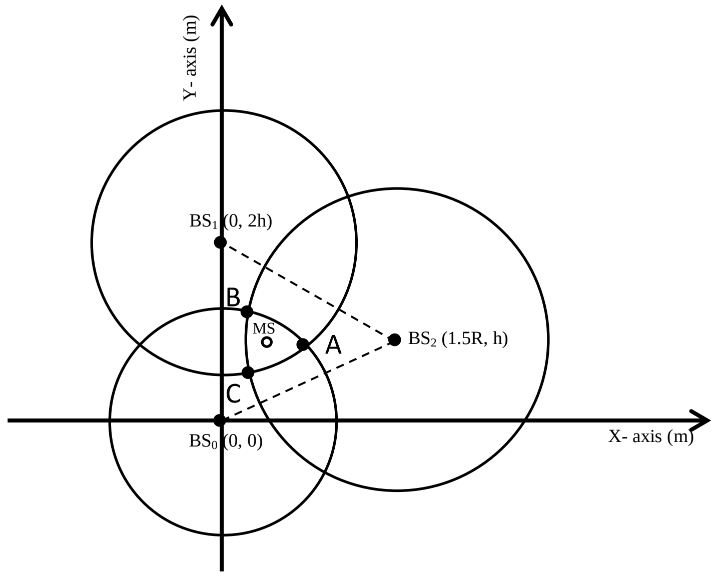

Figure 4. Average positioning method.

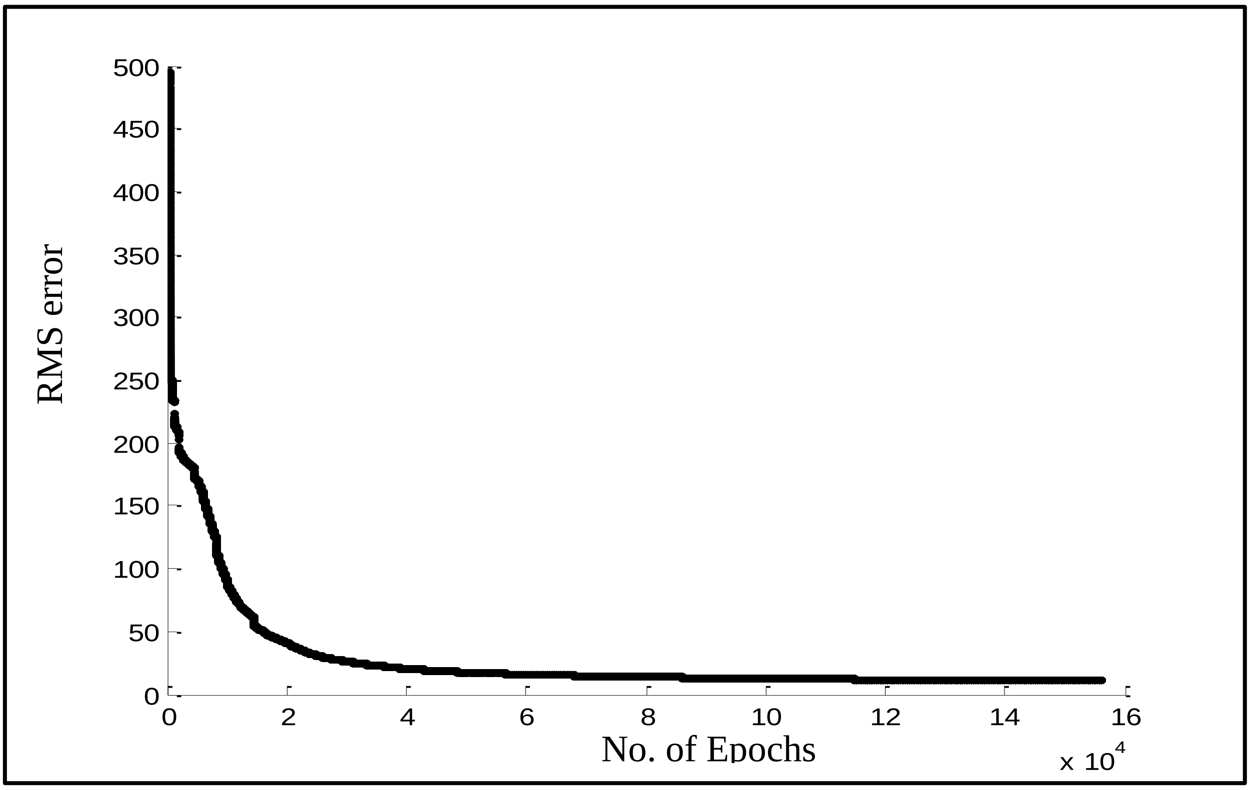

Figure 5. Online training of NN with five neurons in the hidden layer.

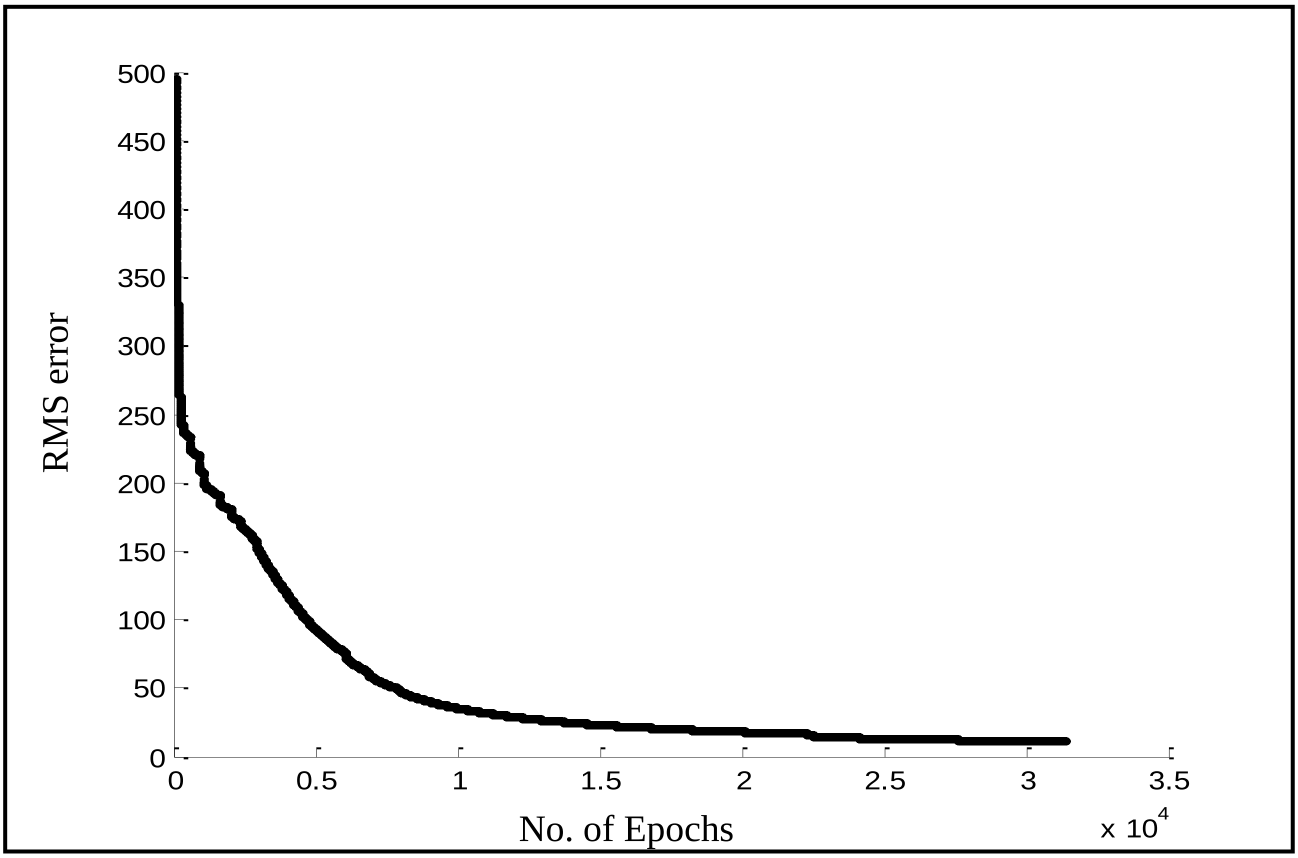

Figure 6. Online training of NN with ten neurons in the hidden layer.

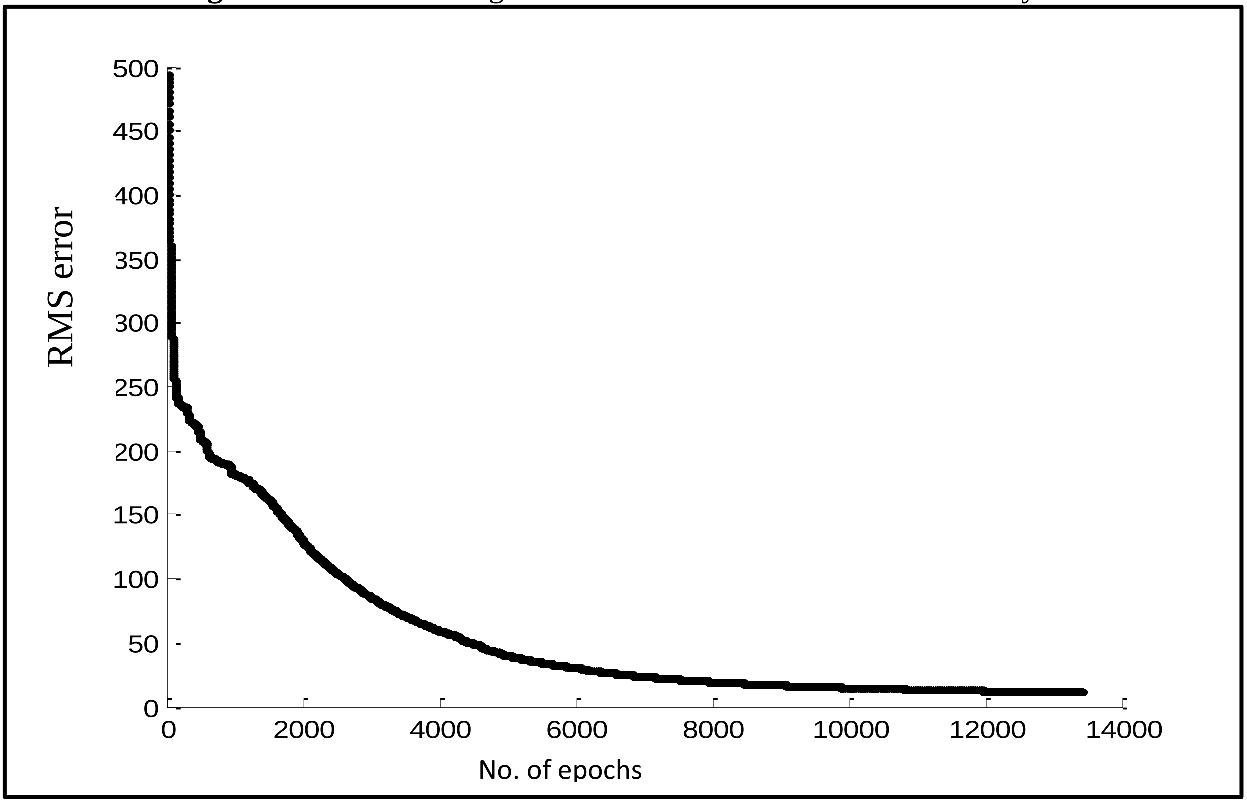

Figure 7. Online training of NN with twenty neurons in the hidden layer.

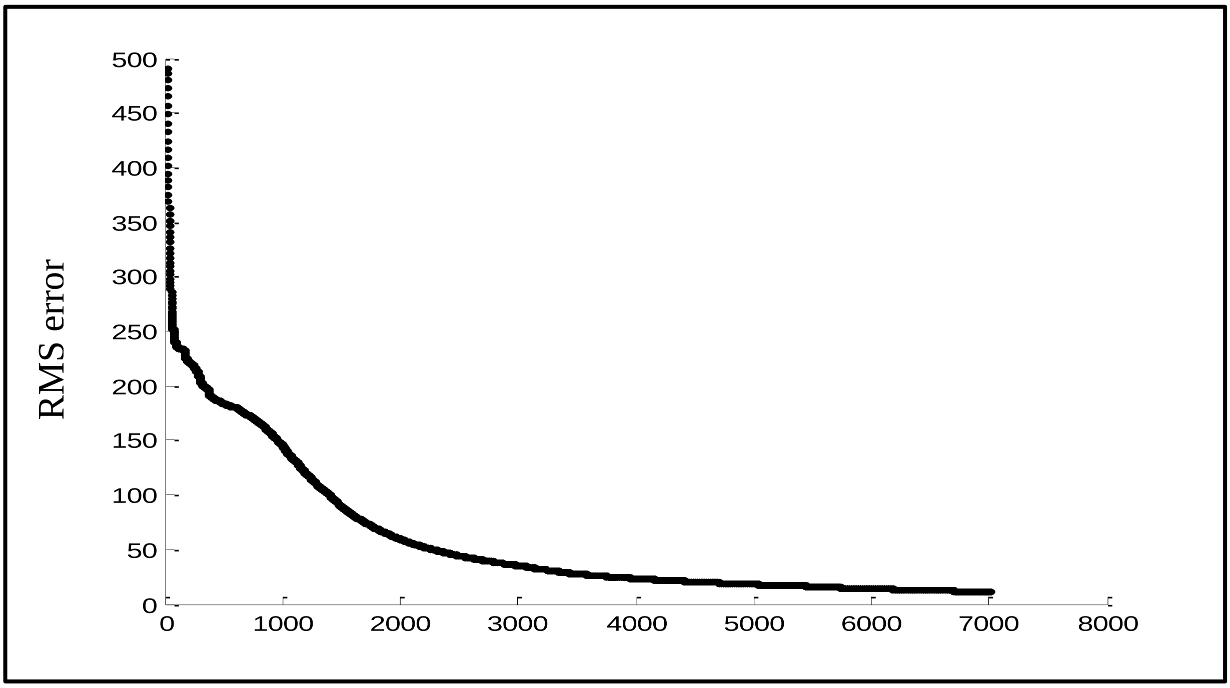

Figure 8. Online training of NN with forty neurons in the hidden layer.

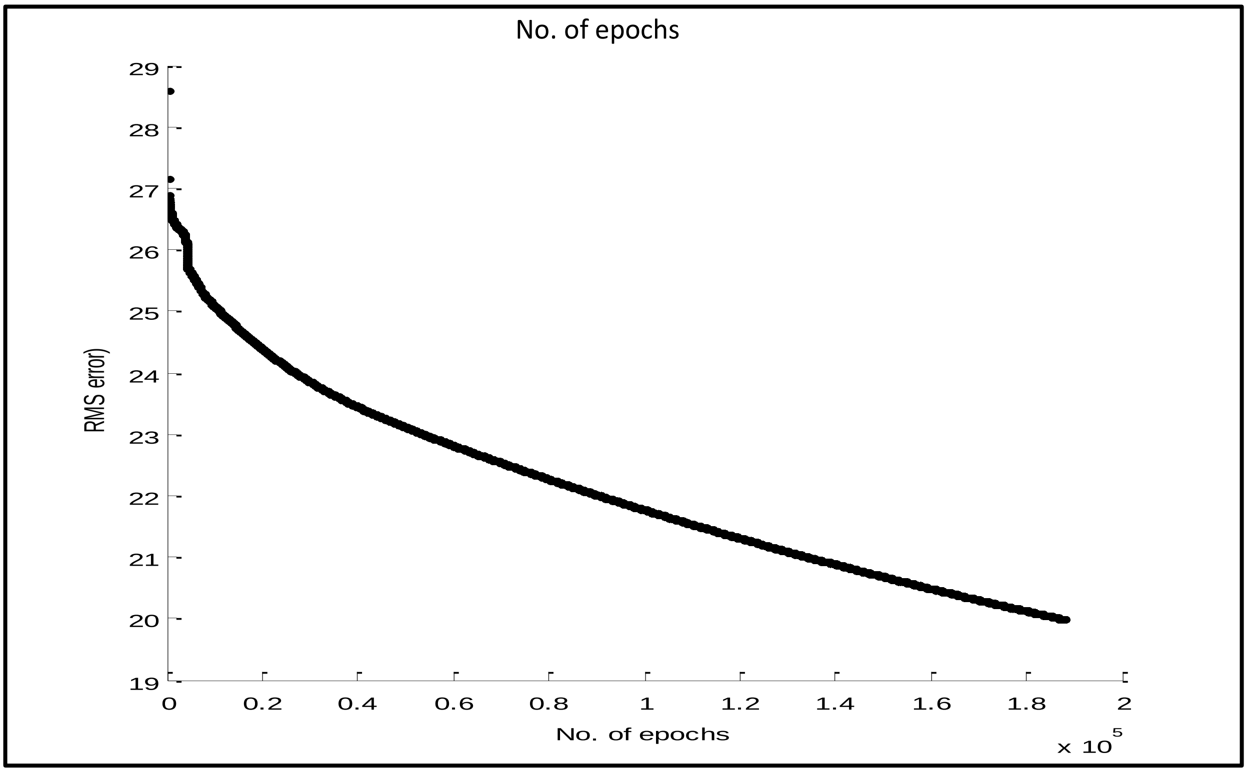

Figure 9. Final step of learning process of forty neurons in the hidden layer for an RMS error value of 20 with $k = 2$ and $\sigma = 2$.

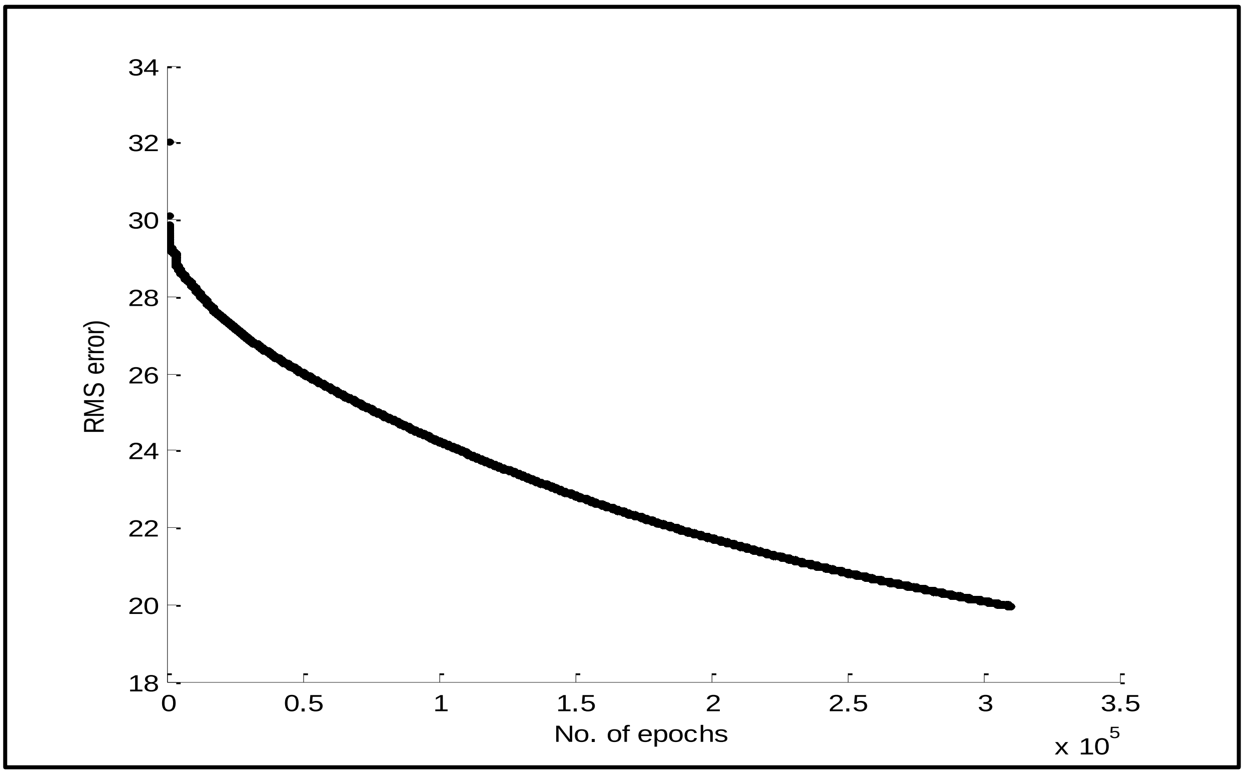

Figure 10. The final step of learning process of forty neurons in the hidden layer for an RMS error value of 20 with $k = 2$ and $\sigma = 4$.

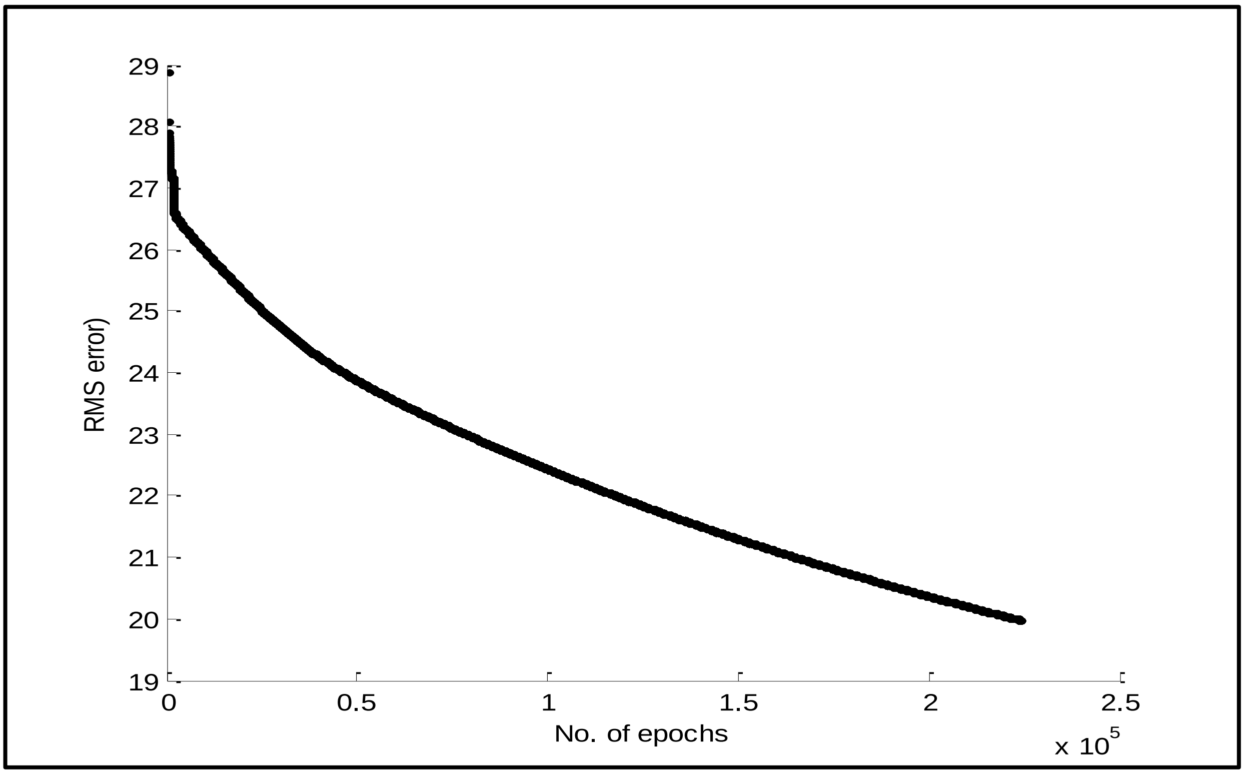

Figure 11. The final step of learning process of forty neurons in the hidden layer for an RMS error value of 20 with $k = 2$ and $\sigma = 6$.

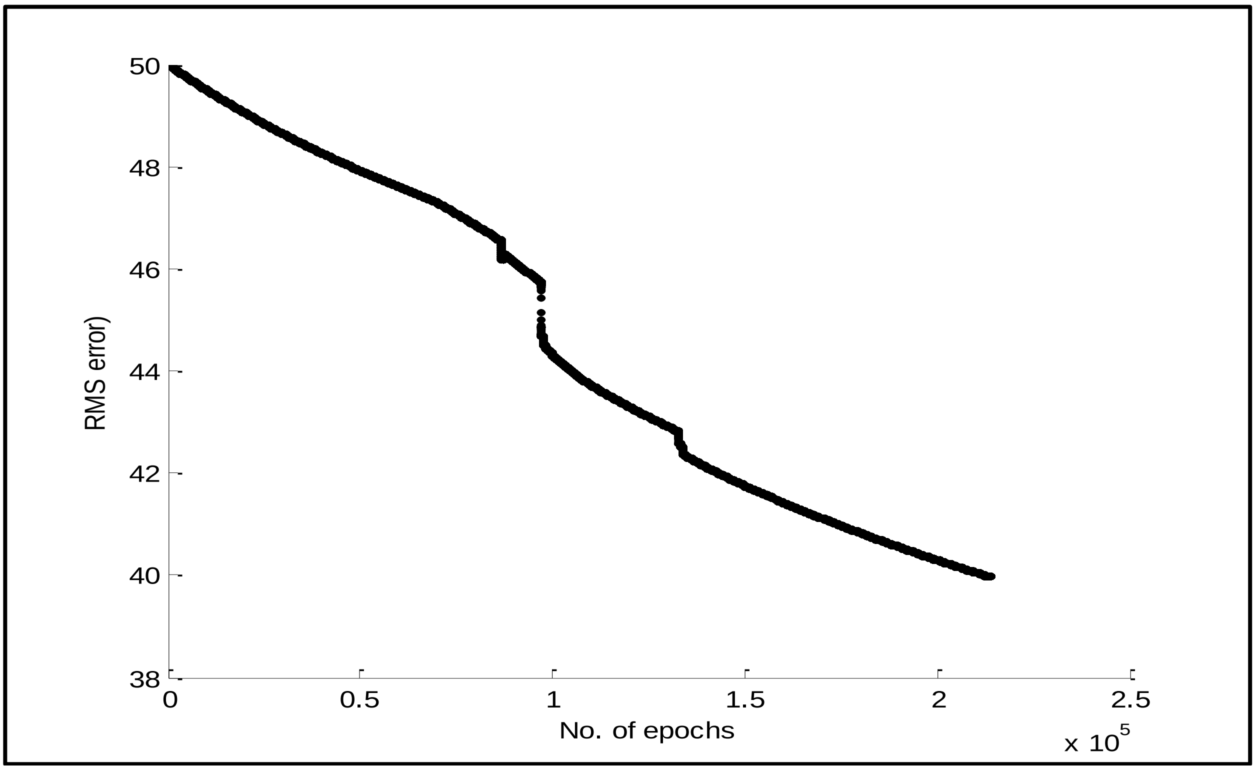

Figure 12. The final step of learning process of forty neurons in the hidden layer for an RMS error value of 40 with $k = 4$ and $\sigma = 2$.

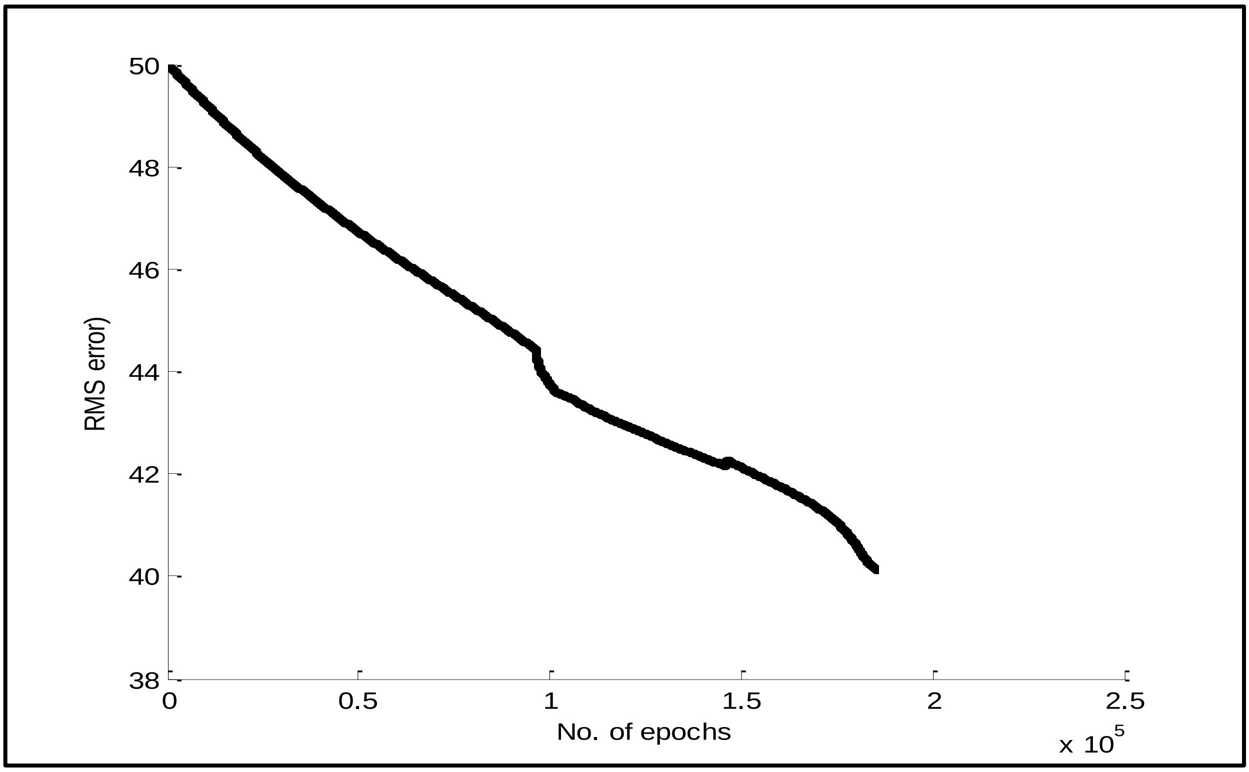

Figure 13. The final step of learning process of forty neurons in the hidden layer for an RMS error value of 40 with $k = 4$ and $\sigma = 4$.

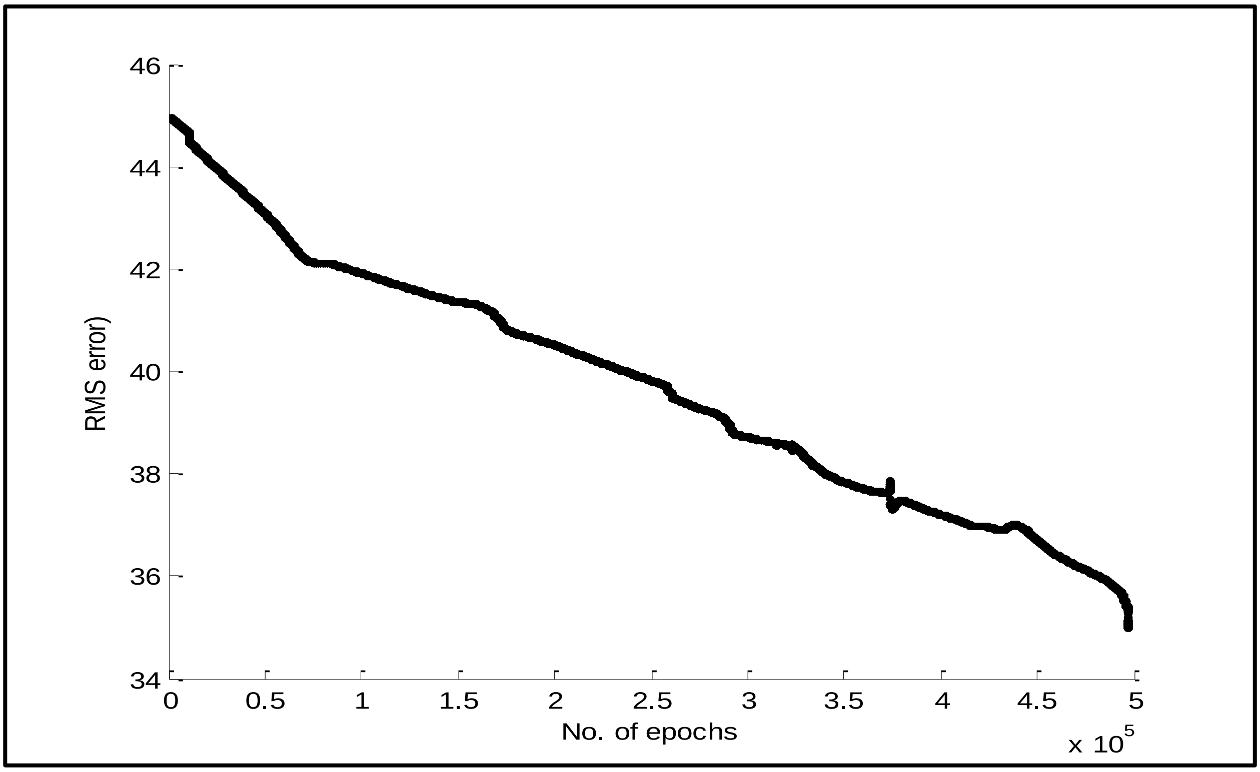

Figure 14. The final step of learning process of forty neurons in the hidden layer for an RMS error value of 35 with $k = 4$ and $\sigma = 6$.

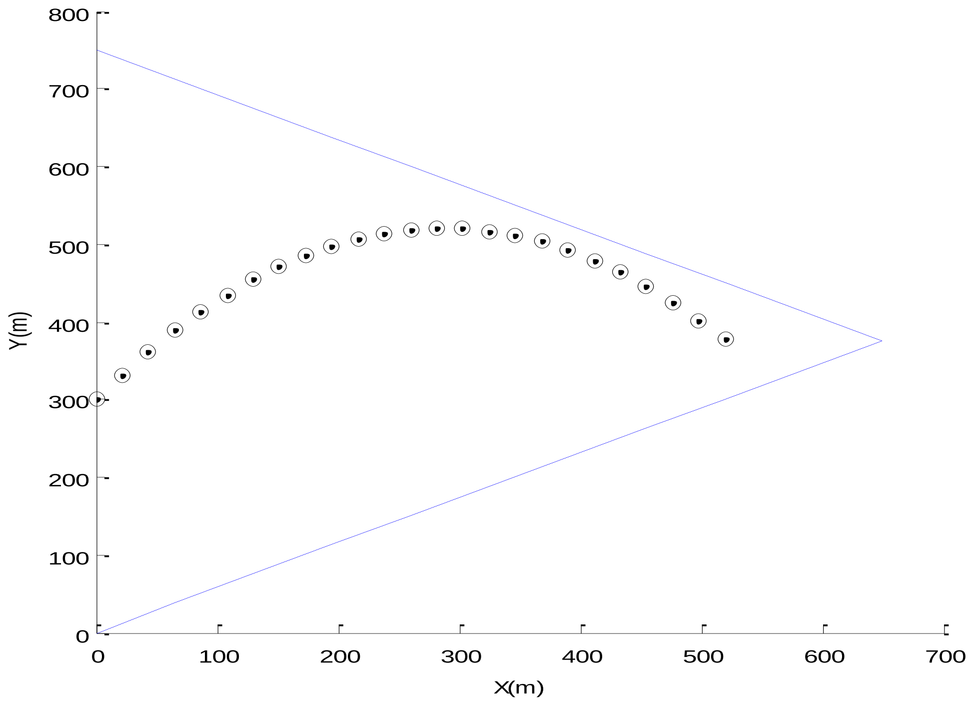

Figure 15. The testing path.

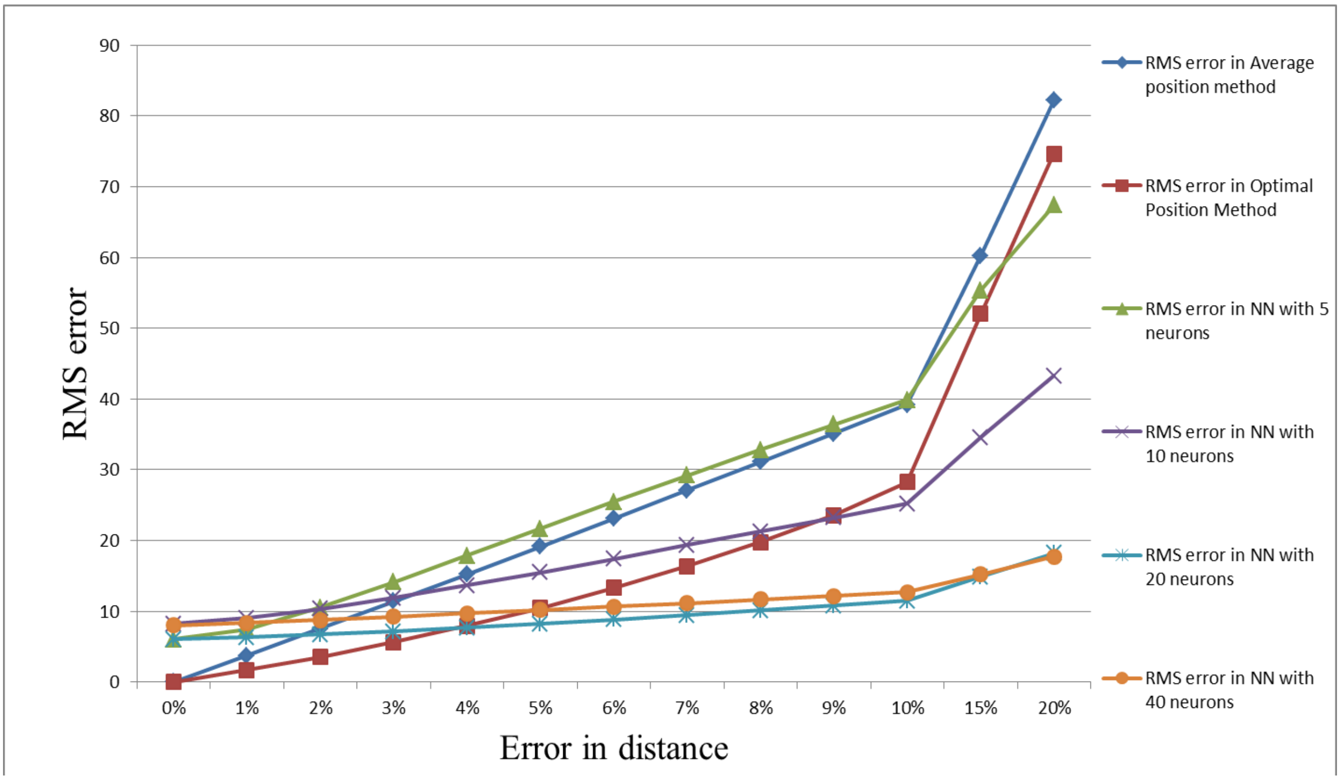

Figure 16. A comparison of NN with four different values of neurons with the average position method and the optimal position method.

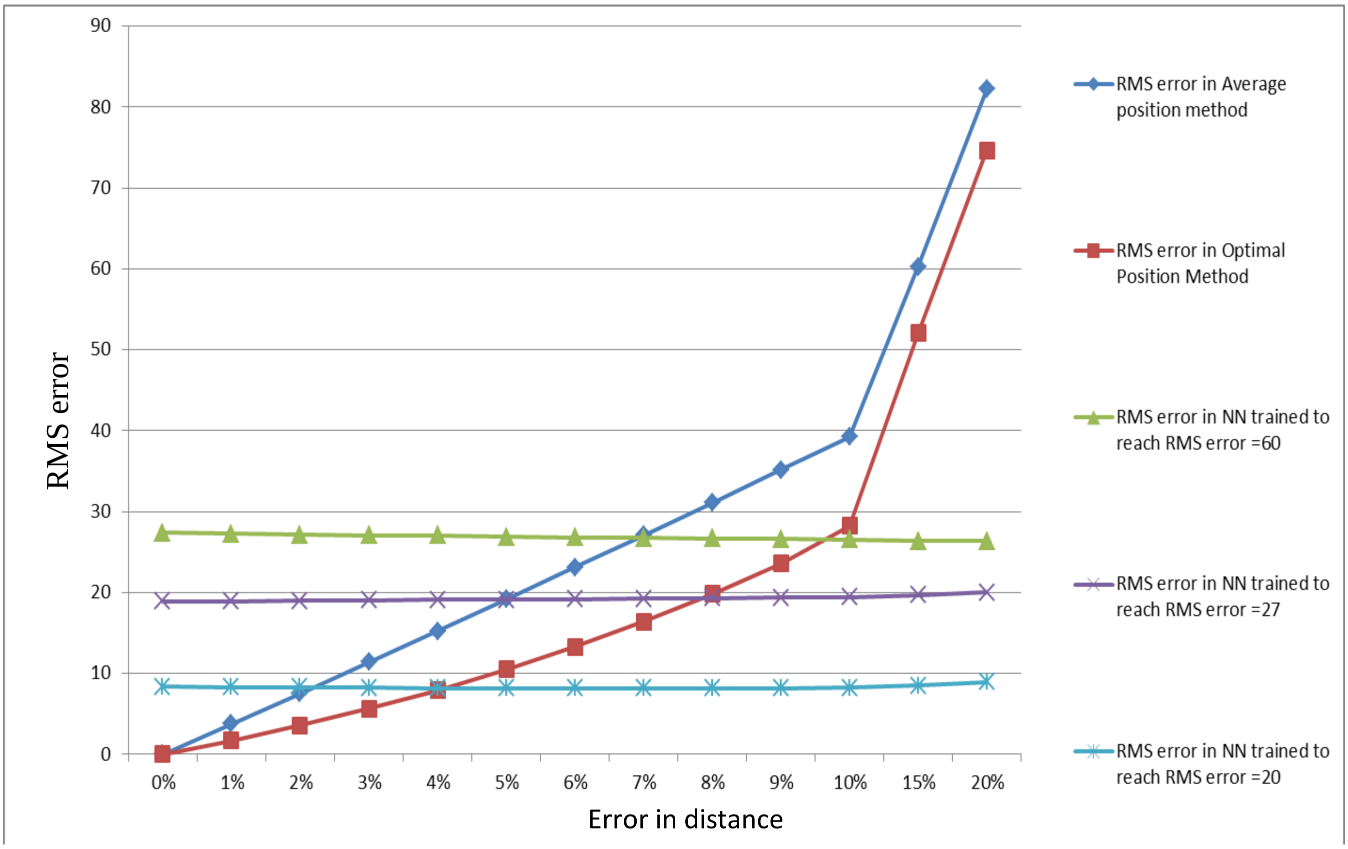

Figure 17. A comparison of NN of forty neurons (k =2 and σ =2) with the average position method and the optimal position method.

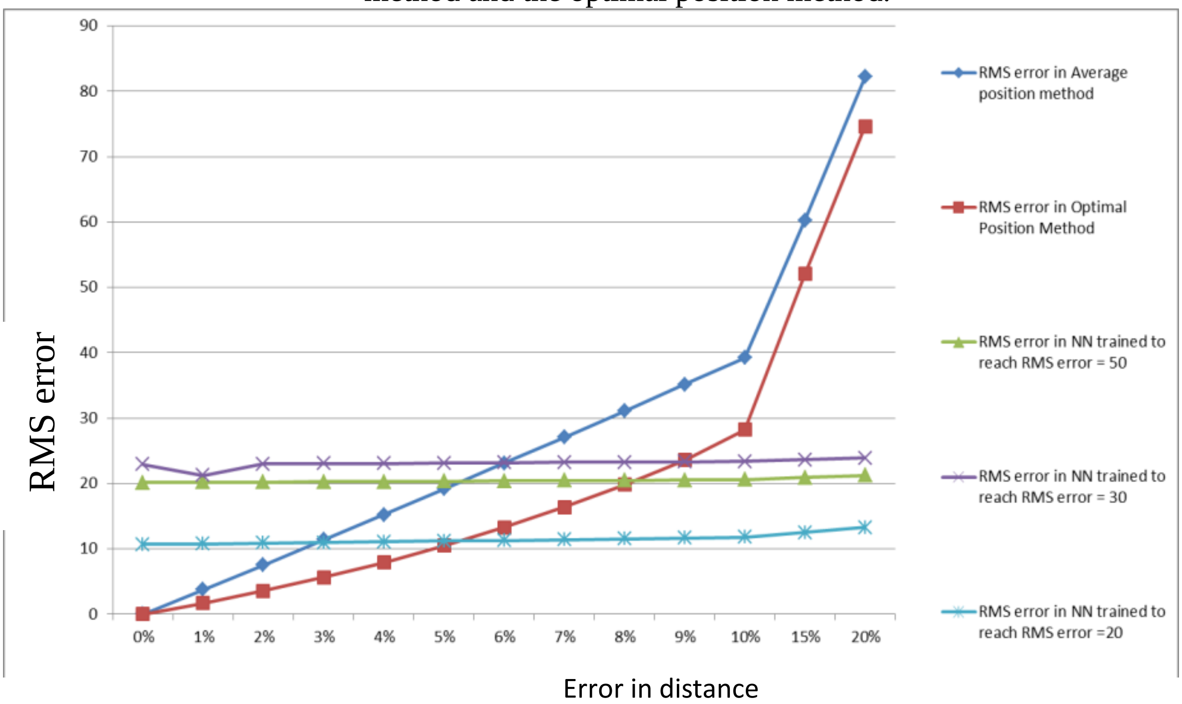

Figure 18. A comparison of NN of forty neurons (k =2 and σ =4) with the average position method and the optimal position method.

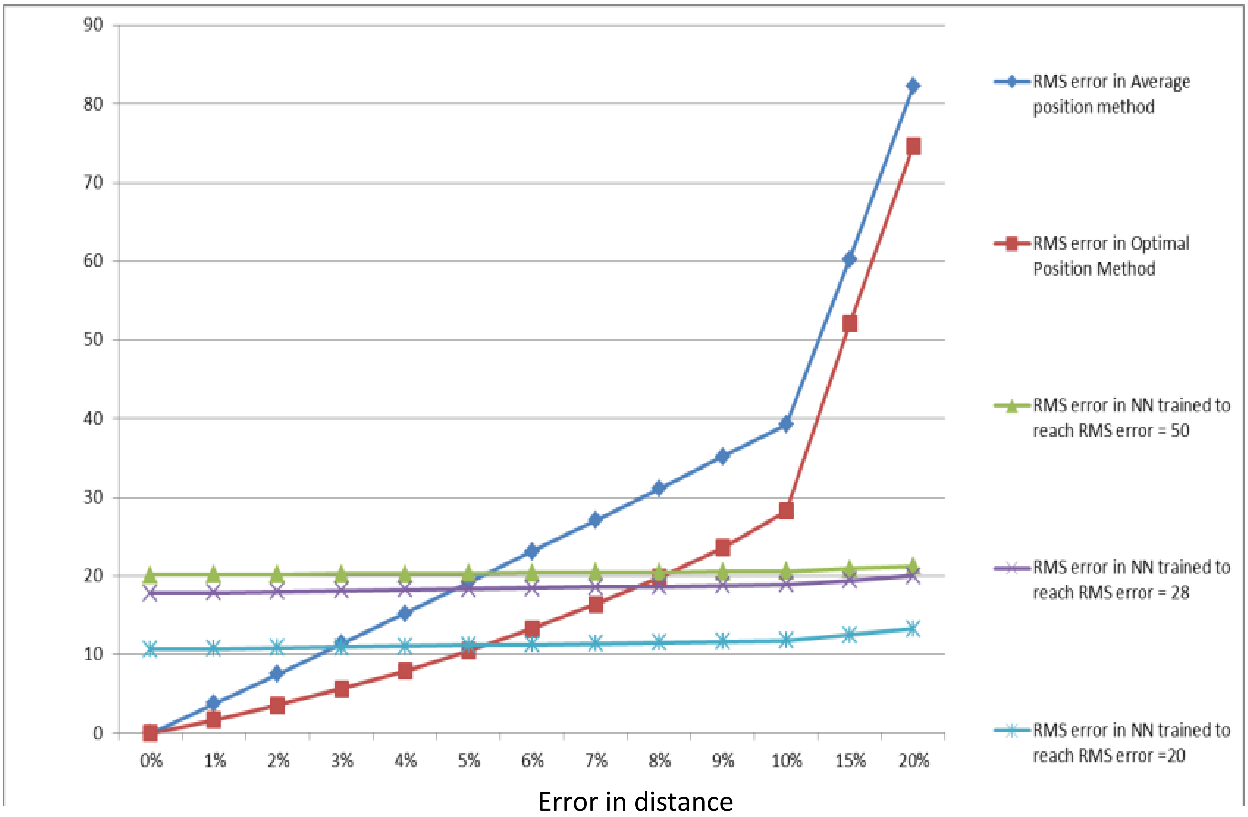

Figure 19. A comparison of NN of forty neurons (k =2 and σ =6) with the average position method and the optimal position method.

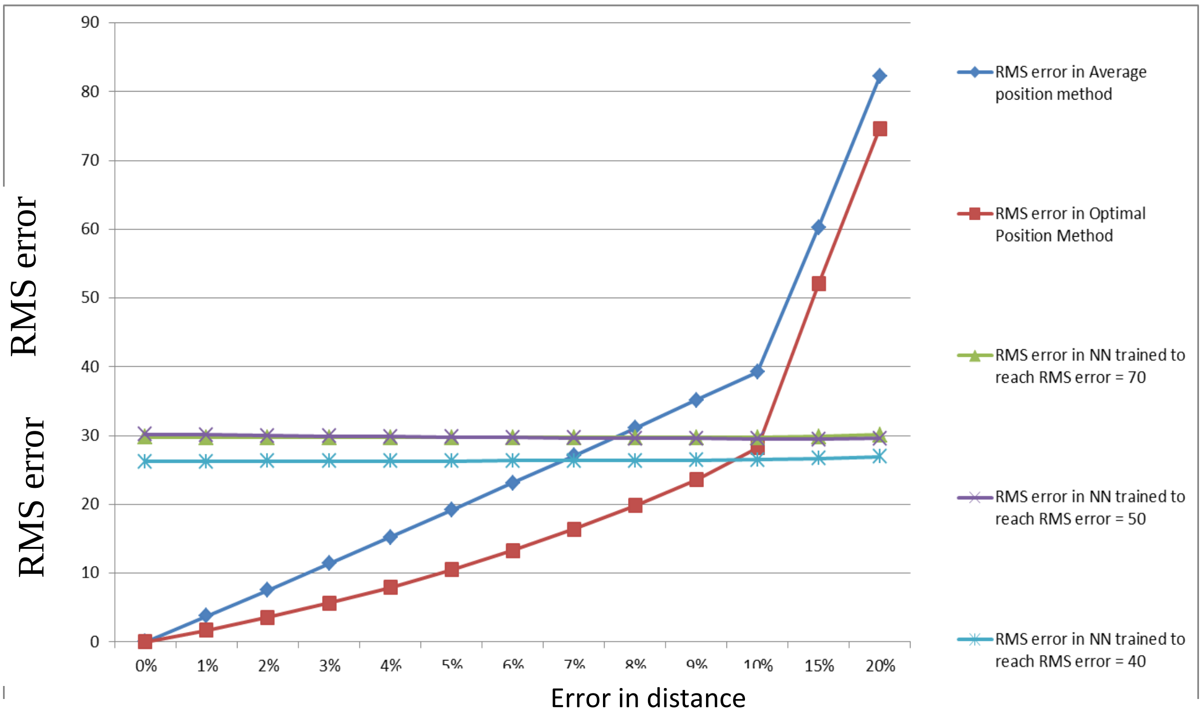

Figure 20. A comparison of NN of forty neurons (k =4 and σ =2) with the average position method and the optimal position method.

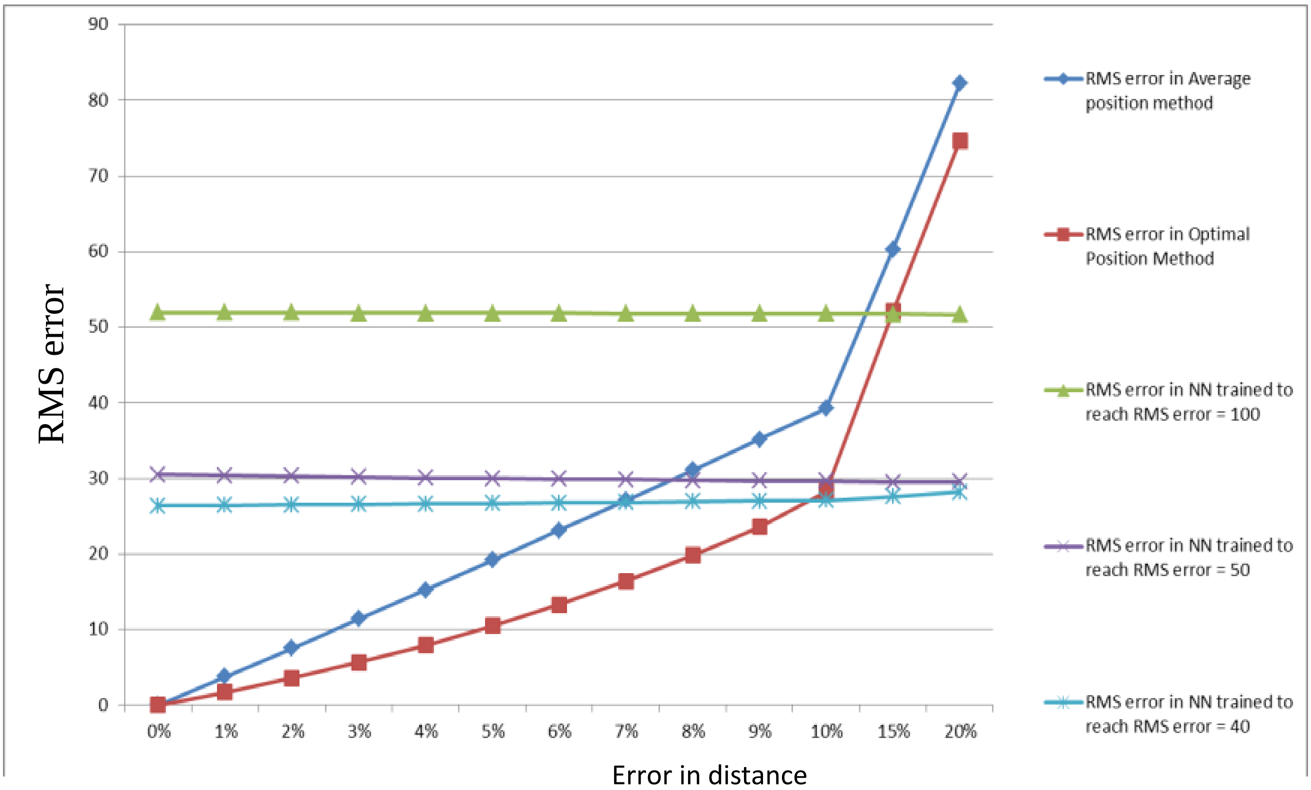

Figure 21. A comparison of NN of forty neurons (k =4 and σ =4) with the average position method and the optimal position method.

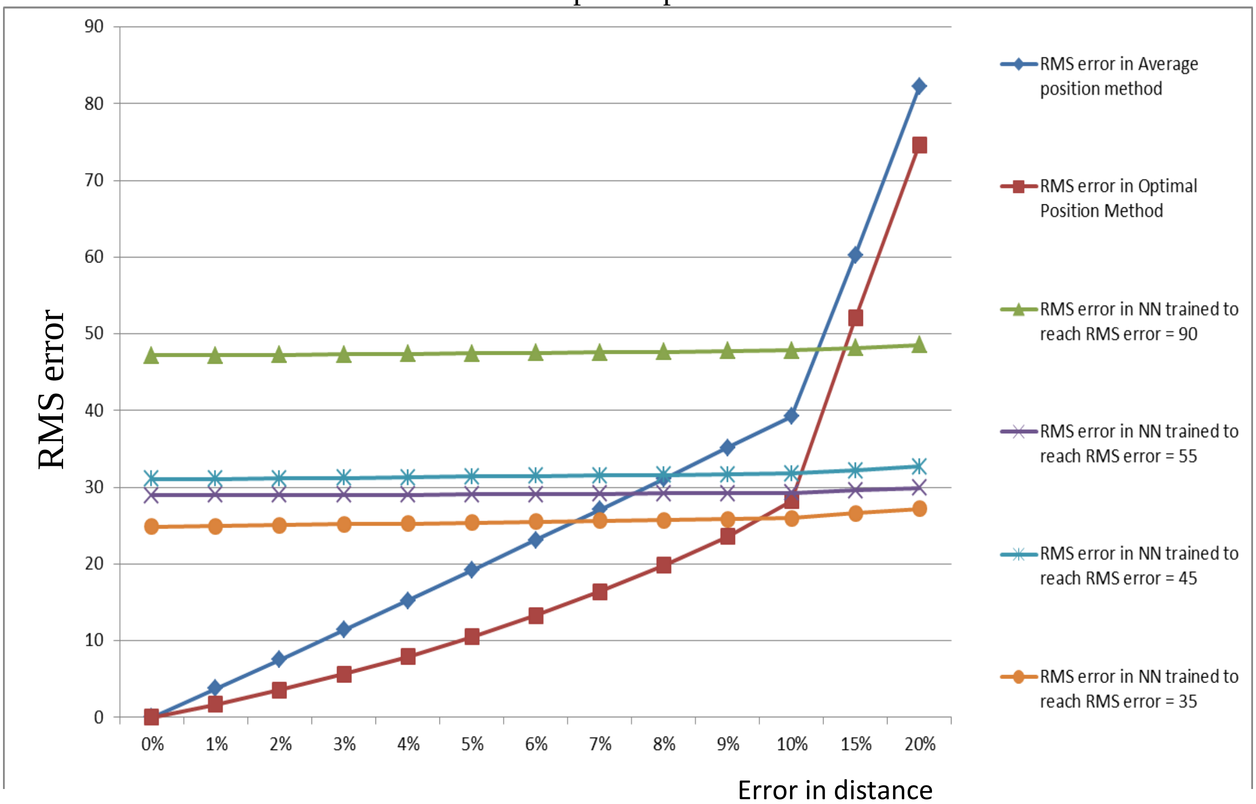

Figure 22. A comparison of NN of forty neurons (k =4 and σ =6) with the average position method and the optimal position method.